ESSAYS IN ENVIRONMENTAL AND ENERGY ECONOMICS

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Traditional studies in economics assume that decision makers are homogeneous. Although this assumption simplifies analysis, modeling decision maker heterogeneity yields insights about consumer or producer behavior that provide policy makers with efficient policy designs. In my dissertation, I analyze how decision maker heterogeneity influences the efficiency of instrument choice in environmental and energy policies. In my first chapter, I consider the efficacy of different policies for increasing fuel economy when households are heterogeneous in how they value gasoline costs when buying a new vehicle. I find that designing policies to target households that undervalue fuel costs can reduce compliance costs of energy efficiency programs in the transportation sector. In my second and third chapters, I evaluate the efficacy of alternative instruments for alleviating adverse selection in markets for carbon offsets when potential projects have heterogeneous characteristics. In these essays, I find that the most efficient policies directly attack the adverse selection problem by lowering baselines to all projects. This is because conservative baselines lead to fewer projects being over-credited and to more projects being under-credited. Taken together, my essays push forward the literature on instrument choice in the face of decision maker heterogeneity and yield general insights for designing sound environmental and energy policy.

BIOGRAPHICAL SKETCH

I was born and raised in Norfolk, Virginia where I graduated from high School as captain of the varsity soccer team. As a freshman in college, I became passionate about economics after attending my first lecture in microeconomics taught by Allen Osman at Ohio State University. Since then I have been devoted to studying and learning about economics and how it can be used to solve significant problems facing humanity. In college, I was initially attracted to the sub-fields of environmental and resource economics as they focused on daunting, global problems, including the depletion of resources and global warming. Since the beginning of my studies at Cornell, I have focused primarily on the latter problem, although both are intertwined in important ways.

I am graduating from Cornell with a Ph.D. in Environmental Economics from the Dyson School of Applied Economics and Management. I have secured a job as a fellow at Resources for the Future (RFF), a think thank in Washington D.C. that devotes its research efforts toward solving environmental and resource policy based problems. I am grateful for the opportunity to work at RFF because we share the same vision and research focus. I look foward to flourishing as a researcher and sharing meaningful and productive collaborations with other fellows there.

This document is dedicated to my family, to my dissertation committee and to all those who have helped me become who I am today.

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I cannot stress enough how much my girlfriend, Beth Spink, and my family, including my mom, dad, brother, sister, brother in law and step-father, helped me survive the gauntlet that is writing a dissertation. They have provided unparalleled psychological and emotional support. They were always available for advice and provided me with unconditional love, regardless of the circumstances. I found it extremely helpful to communicate my research problems with them. I especially thank my mom and Beth. They were always available to talk about my work and frustrations and each contributed clever ways of addressing issues that I faced in my dissertation.

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CHAPTER 1

INTRODUCTION

This dissertation is composed of four chapters. The first chapter provides an overview of my dissertation and summarizes the key results of the proceeding chapters. The remaining chapters are united with the goal of evaluating public policies in the face of decision maker heterogeneity. The first chapter, which I title "Consumer Heterogeneity and the Energy Paradox," analyzes how households value energy efficiency when they buy a new car. The second chapter, titled "Designing Efficient Markets for Carbon Offsets With Distributional Constraints," studies the relative efficacy of three policies – baselines, trade ratios and limits – for alleviating the problem of adverse selection in markets for carbon offsets. The third chapter, currently titled "On the Importance of Baseline Setting in Markets for Carbon Offsets," evaluates the relative magnitudes of over-credited, non-additional offsets and under-credited emissions reductions.

1.1 Summary of "Consumer Heterogeneity and the Energy Paradox"

This paper presents an analysis of the energy paradox – the idea that consumers undervalue cost savings from investments in energy efficiency – with a focus on how consumers vary in their preferences for energy cost savings. By formulating a mixed logit discrete choice model of new vehicle demand that accounts for unobserved product characteristics, I estimate the distribution of household willingness-to-pay (WTP) for reducing gasoline costs by one dollar. While I find that the average household puts equal weight on vehicle price and fuel cost, I find significant heterogeneity in WTP where a non-trivial fraction of households appear to be inattentive to fuel cost differences. Encouraging these households to fully value fuel costs generates welfare gains that are on the same order of magnitude as the cost of increasing fuel economy standards. By calibrating a simple model of the new vehicle market, I find, however, that existing policies for increasing fuel economy fall short of realizing these gains because the policies influence the purchase decisions of all households, including those that fully or overvalue fuel costs. I also find tremendous variation in the ability of existing policies to preferentially encourage households that undervalue fuel costs to buy more fuel efficient vehicles, which highlights the importance of understanding and evaluating how energy efficiency programs target different consumer types.

1.2 Summary of "Designing Efficient Markets for Carbon Offsets With Distributional Constraints"

This paper presents an assessment of the relative efficacy of three key instruments - baselines, trade ratios and limits - which are under policy discussion in the design of carbon offset programs. We rank the instruments by their implications for total emissions, economic efficiency, and efficiency gain relative to a distributional transfer from capped to uncapped sectors. We find that the baseline is the best instrument for maximizing welfare as it directly reduces the share of offsets that are non-additional and that second-best policies do not sacrifice much welfare relative to the standard first-best policy prescription.

1.3 Summary of "On the Importance of Baseline Setting in Markets for Carbon Offsets"

Incorporating carbon offsets in the design of cap-and-trade programs remains a controversial issue because of its potential unintended impacts on emissions. At the heart of this discussion is the issue of crediting of emissions reductions. Projects can be correctly, over- or under-credited for their actual emissions reductions. We develop a unified framework that considers the supply of offsets within a cap-and-trade program that allows us to compare of the relative impact of over-credited offsets and under-credited emissions reductions on overall emissions under different levels of baseline stringency and carbon prices. In the context of the 2009 Waxman-Markey legislation, we find that the emissions impacts of over-credited offsets can be fully balanced out by under-credited emissions reductions without sacrificing a significant portion of the overall supply of offsets, provided emissions baselines are stringent enough. Under a medium-run reduction target of two billion tons of CO_2 equivalent, to maintain the environmental integrity of the program, baselines need to be set to 70 percent of predicted business-as-usual (BAU) emissions. Moreover, as the carbon market achieves higher equilibrium prices, less stringent baselines can balance out the emissions impacts of over-credited offsets and under-credited emissions reductions.

CHAPTER 2

CONSUMER HETEROGENEITY AND THE ENERGY PARADOX

2.1 Introduction

Climate change and energy security are two key public policy issues facing the United States today. These issues have focused the attention of policy makers on designing and evaluating programs that reduce greenhouse gas emissions and energy consumption. Some examples in the transportation sector include hybrid vehicle subsidies, Corporate Average Fuel Economy (CAFE) standards and gas guzzler taxes. These policies are designed to encourage the sale of energy efficient, high miles-per-gallon (MPG) vehicles with the dual goal of reducing greenhouse gas emissions and gasoline consumption.

Understanding how consumers value energy efficiency is crucial for evaluating the costs and benefits of these policies and determining which policies have the lowest welfare costs for reducing energy use and internalizing the externalities associated with energy consumption. For example, Sallee [100] compares the costs and benefits of reformed Corporate Average Fuel Economy (CAFE) standards under two scenarios: one where consumers fully value fuel cost savings from buying high MPG cars, and one where they do not internalize these savings. He finds that the new CAFE standards fail to pass a cost-benefit test in the former case but pass the test in the latter case.[1] In other words, quantifying

[1] This result appears in Table 1 in [100]. For the time frame between 2012-2016, CAFE standards

the private fuel cost savings created by the program as an external benefit of the program is necessary for the policy to pass a cost-benefit test. If consumers fully value fuel cost savings, then the program fails the test.

In this paper I estimate how households in the United States value fuel cost savings when they make a new vehicle purchase. In contrast to most existing literature in this area, I estimate the entire distribution of household preferences for fuel economy. This allows me to investigate whether households are heterogeneous with respect to their valuation of fuel costs. Whether some consumers undervalue fuel cost savings while others do not has crucial implications for designing efficient energy policy. An efficient policy will be able to preferentially encourage the consumers that undervalue to buy more efficient vehicles. A policy that primarily encourages households that already fully value energy costs can be thought of as attracting the wrong sub-group of the population. This targeting problem is common in many other climate and energy related policies, including carbon offset programs [15], electricity rebate programs [68] and flexibility mechanisms in cap-and-trade programs [90].

I use two datasets to estimate the distribution of household preferences for fuel economy. The first dataset comes from R.L. Polk and comprises new vehicle shares at the Metropolitan Statistical Area Level. I merge these share data with detailed household demographics and vehicle holdings data from the two most recent waves of the National Household Transportation Surveys. These data allow me

cost 346 billion dollars and bring external benefits of 312 billion dollars. Fuel savings benefits, however, are $1,546$ billion dollars.

accurately estimate household consumer preferences for fuel economy and other vehicle characteristics that are relevant to the consumer purchase decision.

I estimate a mixed logit new vehicle demand model that includes a separate parameter for present value lifetime vehicle fuel costs and vehicle price. I model the parameter for the present value of lifetime vehicle fuel costs as random, allowing households to have different valuations of fuel costs. To account for unobserved vehicle characteristics, I estimate vehicle model fixed effects using a modified version of the contraction mapping approach described in [19]. I show that including these fixed effects is crucial for obtaining unbiased estimates for WTP since they control for vehicle price endogeneity.

To estimate the distribution of willingness-to-pay for reducing fuel costs by one dollar, I take estimated parameters for the random utility model and compute the ratio of the marginal utility of fuel costs and the marginal utility of price. I find that on average, households fully value fuel cost savings as they are willing to pay about 98 cents to reduce the present value of fuel costs by one dollar. Importantly, however, I find that there is substantial heterogeneity in how the sample of households value fuel costs. The estimation results suggest that about 31 percent of households ignore fuel costs when they make a new vehicle purchase.

To evaluate the implications of this heterogeneity, I calibrate an equilibrium model of the new vehicle market with the estimated econometric parameters of consumer preferences. I find that a policy that only targets households that undervalue fuel costs to buy more fuel efficient vehicles creates private welfare gains that can be as large as or exceed the costs of increasing fuel economy standards. I then simulate how well three existing policies for increasing fleet fuel economy – a gas guzzler tax, a feebate and a fuel efficient vehicle subsidy – are able to target these consumers. The simulation results suggest that none of the policies are effective at primarily influencing the purchase decisions of households with WTP less than one. Furthermore, I find that the ability to target households that undervalue fuel costs substantially differs across policies. The gas guzzler tax is best at preferentially encouraging households that undervalue to buy more fuel efficient cars. This is because the tax only applies to vehicles that are likely to be bought by households that undervalue fuel costs. The subsidy policy, on the other hand, is poor at targeting. For a common increase in fuel economy, a subsidy to efficient vehicles increases private welfare internality benefits by about one-third of the increase from an equivalent gas guzzler tax. The subsidy is poor at targeting because it only applies to vehicles that are already likely to be bought by households that fully value fuel economy. With these results in hand, I argue that the consumer heterogeneity in fuel cost valuation has significant implications for evaluating several other policies in the transportation sector, including vehicle scrappage programs and reformed footprint-based standards.

The rest of the paper is organized as follows. In Section 2.2, I review relevant research in the areas of consumer valuation of fuel economy and policy analysis of energy efficiency programs. In Section 2.3, I set out the ingredients of the empirical model that I use to estimate WTP for reducing fuel costs by one dollar. In Sections 2.4 and 2.5, I discuss the data and estimation results of the empirical model, respectively. I then present a policy analysis in Section 2.6 that includes a simulation model that is calibrated to the econometric parameters. I make concluding remarks in Section 2.7.

2.2 Literature Review

My paper contributes to two related areas of energy and environmental economics. The first area involves estimating how consumers trade off higher up-front purchase prices for lower lifetime energy costs of durable goods. This trade-off is usually presented as a measure of willingness to pay. The literature on estimating consumer willingness to pay for lower energy costs from observed purchase decisions of durable goods begins with [63]. In this paper, the author estimates a model of consumer choice for air conditioners. Hausman includes variables for the product's upfront purchase price and the present value of operating costs. He keeps as a free variable the consumer discount rate and uses this variable to rationalize estimated consumer preferences for price and operating costs.[2] Hausman finds an implied discount rate of 26.4 percent, which lies well above private interest rates on loans for air conditioners. This finding initially suggested that consumers undervalue energy costs when making durable good purchase decisions.

Since Hausman's seminal work, dozens of papers have estimated how

[2] [63] calculates the implied discount rate by adjusting this value until the change in utility from a change in operating costs is constant for a one dollar change in the purchase price.

consumers value energy costs in other sectors of the economy, including transportation. Greene [58] reviews and summarizes 25 studies that estimate how consumers value miles per gallon fuel economy, which is the standard expression for energy efficiency in automobiles.[3] He finds that estimates for WTP for reducing fuel costs by one dollar are all over the place: they range from less than one penny ([19] e.g. consumers on average ignore fuel costs when buying a car), to about one dollar ([35], [41], e.g. consumers fully value fuel cost savings), to over one thousand dollars ([117], e.g. consumers put a very high value of energy savings). Out of the 25 there are more studies, however, that imply that consumers undervalue than there are that imply that consumers overvalue.[4]

Recent studies, however, appear to agree that households either fully value or modestly undervalue energy costs when making car purchase decisions. Sallee et al. [102] use micro data on used vehicle prices, odometer readings and gasoline prices to estimate the relationship between fuel costs and vehicle prices. They find that consumers value one dollar of fuel savings at 79 cents. This valuation, however, is not statistically different from full valuation.

Allcott and Wozny [5] and Busse et al. [28] use the large variation in gasoline prices between 1999 and 2008 to estimate the relationship between gasoline prices and car prices. They find that when gasoline prices rise, the relative prices of high

[3]Some believe that energy efficiency in automobiles should be reported in gallons per mile which is the inverse of miles per gallon. Doing so would allow consumers to better gauge fuel cost savings from buying more fuel efficient vehicles [79, 3].

[4]Green groups the studies by econometric methodology to show that studies using hedonic methods find that households either undervalue or fully value fuel cost savings. In contrast, studies using discrete choice methods are evenly distributed among under, full and overvaluation.

MPG cars rise, suggesting that consumers (at least somewhat) value fuel economy. Busse et al. [28] do not directly estimate the WTP for reducing fuel costs by a dollar. Instead they allow the consumer discount rate to be a free variable and solve for it in a similar manner as seen in [63]. For a wide range of assumed demand elasticities, they find that implied consumer discount rates fall within the range of observed interest rates for auto loans. The authors claim that this suggest there is little evidence that consumers are myopic when they buy a car.

Allcott and Wozny [5] derive a simple linear regression model based on a structural discrete choice model that allows them to directly estimate WTP. Using used car auction prices, they find that consumers moderately undervalue fuel economy when they make purchase decisions. They find that consumers are willing to pay 76 cents to reduce the present value of fuel costs by one dollar. Although 76 cents appears close to full valuation, the authors conclude that if this undervaluation stems from a market failure, correcting the failure could generate welfare gains that exceed the gains from internalizing climate change externalities generated from automobile gasoline consumption.

What these studies lack is a detailed treatment of the potential heterogeneity of consumer preferences for fuel economy. This is relevant for policy because if some consumers undervalue fuel economy while others fully value, then targeting may play a key role in designing efficient energy policy in the transportation sector. To the best of my knowledge the only other paper that attempts to estimate consumer heterogeneity for fuel economy is by [104].[5] Sawhill estimates a mixed logit discrete choice model of vehicle demand using aggregate data from 1971 to 1990 to test whether consumers fully value the gasoline cost savings from fuel efficient vehicles. He finds that consumers on average moderately overvalue fuel economy for new vehicles. More relevant to my paper, however, is that his results suggest that there is substantial heterogeneity in how consumers value energy efficiency.

My analysis has several key differences relative to [104]. First, I use newer data that includes several new vehicle types, including SUVs and hybrids. Including these vehicle types in consumer choice sets is likely to have a major impact on the perceived valuation of fuel economy since these vehicles locate in the extremes of the fuel economy distribution for new cars. Second, I estimate my model with household level data linked to aggregate data, which is a more appropriate approach to obtaining accurate estimates for household preference parameters.[6] Third, I estimate parameters for a truncated normal distribution for WTP, which is more suitable for behavioral parameters that should have a non-negative range.[7]

[5] [5] and [102] hint that there is heterogeneity across vehicles. For example, [5] estimate their model for different vehicle ages and find that WTP is typically lower for older vehicles. It is not clear, however, how this relationship translates into heterogeneity across households. Furthermore, they do not attempt to estimate the entire distribution of WTP across their sample, which is a necessary input for policy simulation.

[6] Using household level data also allows me to exploit substantial variation in gasoline prices across households and across time, which helps reduce standard error estimates. Another benefit of household level data is that it makes it possible to estimate WTP for sub-groups of the population to identify whether observed household demographics are correlated with consumer valuations of fuel economy.

[7] Allowing WTP for fuel costs to be unbounded, as in the case of a normal distribution, implies that a fraction of the population prefers higher fuel costs. One common method to deal with this issue is to estimate a fixed parameter for WTP. Alternatively I estimate the entire distribution of

A fourth difference is that I take the estimated distribution for WTP and run several simulation exercises to assess its policy implications.

In addition to estimating the distribution of WTP for fuel cost reductions, I evaluate the implications of the estimated distribution for the efficiency of alternative energy efficiency policies. Previous work has traditionally focused on comparing CAFE standards (or an equivalent fuel efficiency subsidy) to gasoline taxes. Using a calibrated numerical general equilibrium model [46] shows that gasoline taxes are a much more efficient method of reducing gasoline consumption since they encourage the reduction of gasoline consumption on several channels of adjustment, including purchasing more fuel efficient cars and reducing vehicle miles traveled. CAFE standards are generally inefficient because they encourage households to drive more.[8] Jacobsen [70] arrives at a similar conclusion after simulating a multi-market equilibrium model that is calibrated based on a sophisticated discrete choice model of vehicle demand. Fischer et al. [46] finds, however, that if consumers dramatically undervalue fuel economy, then CAFE standards are a more efficient method of reducing gasoline use.[9]

Allcott et al. [4] evaluate the optimal simultaneous choice of gasoline taxes and fuel efficient vehicle subsidies when consumers undervalue fuel costs. They find that there is a rationale for including fuel efficient vehicle subsidies in

WTP by assuming that WTP is bounded from below at zero so that no households obtain positive utility from higher fuel costs (while holding other vehicle characteristics fixed).

[8]This is because CAFE standards increase fleet fuel economy, which reduces average vehicle per mile operating costs.

[9]If the entire population ignores fuel costs, increasing the price of gasoline will not influence new vehicle purchase decisions.

the optimal policy mix when consumers privately mis-optimize their vehicle purchase decisions. The rationale is simple: The gasoline tax is primarily used to internalize gasoline use externalities, while the fuel efficient vehicle subsidy is used to correct the private mis-optimization.[10] Allcott et al. [4] also consider the optimal combination of gasoline taxes and fuel efficient vehicle subsidies when consumers are heterogeneous in their valuation of energy costs. As consumers become more heterogeneous, the optimal combination of instruments performs worse. This is because neither policy is well equipped to target consumers that undervalue fuel costs. I extend these results in my analysis by comparing existing policies in the transportation sector that potentially have different abilities to encourage the different types of consumers to buy more fuel efficient cars. Furthermore, I calibrate my simulation exercise based on my econometric estimates of the consumer heterogeneity. This proves to be important for contrasting the policies as the econometric estimates imply different demand elasticities for different groups of households.

Other policies have focused primarily on evaluating programs that directly encourage greater energy efficiency. Hausman and Joskow [64] evaluates the efficacy of energy efficiency standards for appliances when consumers are heterogeneous in usage but not valuation of energy efficiency. They find that standards are inefficient for reducing energy use since they do not differentiate between high- and low-utilization consumers. Ito [68] evaluates the cost-effectiveness of California's 20/20 electricity rebate program. He finds that

[10] A related result is derived by Heutel [66] in a model of hyperbolic discounting.

treatment effects of the program are very heterogeneous across the state. The reason for the heterogeneity is that some consumers are so far from the rebate threshold that the policy has little effect on their behavior. Only those that are close or already over the threshold earn the subsidy, implying that many of the rebate payments flow to consumers that are "non-additional."[11] In a sense, Ito [68] finds that the California subsidy is generally poor at targeting consumers that use the most electricity. In contrast to these studies, I evaluate and compare three policies for encouraging energy efficiency. This comparison provides policy makers with some direction for designing more efficient future policies.

A paper that compares multiple policy instruments for increasing energy efficiency is [59]. In this paper, the authors simulate the market effects of feebates, rebates and gas-guzzler taxes. They find that a feebate is the most efficient method of increasing fleet fuel economy because it applies to all vehicles. This result is consistent with my simulation results. I extend these results by allowing households to have different valuations for fuel economies based on an empirical model that I specify in the next section.

[11] "Non-additionality" is a term most commonly associated with markets for carbon offsets, where the meaning is for offset projects that would have happened without a carbon payment.

2.3 Empirical Model

In this section I present the empirical specification for estimating the distribution of household willingness-to-pay (WTP) for reducing the present value fuel costs. I adopt a mixed logit discrete choice framework for obtaining WTP estimates across the sample of households considered. A primary reason for using a discrete choice framework – opposed to alternative methods such as hedonic pricing – is that I can directly substitute the parameter estimates into a simulation model of the U.S. automobile sector that I can then use to run counter-factual policy simulations.

Adopting a mixed logit framework comes with several features that are crucial for my analysis. The most obvious is that I can estimate the distribution of WTP for several variables including reducing the present value of fuel costs. Another well-known benefit is that mixed logit models allow for more realistic substitution patterns across alternatives [113]. As a consequence, estimated own price elasticities of demand are likely to be more accurately estimated with a mixed logit model. Since WTP is a function of price sensitivity – as the price coefficient enters in the denominator of the WTP expression – a more accurate price elasticity of demand translates into a more accurate estimate for WTP. A third benefit of adopting a mixed logit framework that is germane to estimating how consumers value fuel economy stems from sorting bias. Bento et al. [13] document that sorting is likely to lead to biased estimates for fuel economy valuation in models that do not allow for preference heterogeneity. If consumers are heterogeneous in how they value fuel economy, then those that undervalue fuel economy will sort into vehicles with relatively low MPG and those that correctly (or overvalue) fuel economy will sort into vehicles with relatively high MPG. As a consequence vehicle purchase data will suggest that consumers do not respond much to changes in fuel economy even if they do, leading to a downward bias (in magnitude) for the average valuation of fuel cost savings. Hedonic price models and fixed coefficient logit models will suffer from this bias if in fact consumers are different with respect to how they value fuel efficiency. Bento et al. [13] show, however, that a mixed logit model can correctly recover the average valuation.

I assume that household demand for new vehicles is derived from utility maximization. Formally, each household i derives utility from purchasing new vehicle j in market t according to the utility function

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt}. \tag{2.1}$$

I assume the following structure for V_{ijt}:

$$V_{ijt} = \frac{\alpha}{Inc_{it}} + \gamma\frac{p_{jt}}{Inc_{it}} + \beta_i\frac{fc_{ijt}}{Inc_i} + \theta_i' X_{ijt} + \delta_{jt}. \tag{2.2}$$

The first term is the inverse of household income (Inc_{it}), which allows households with low income to have a larger marginal utility of income. The second term has a fixed coefficient γ for vehicle price (p_{jt}) as a fraction of household income. This term measures how consumers of different income classes have different price sensitivities. The third term has a random coefficient β_i for household i's present value of vehicle j fuel costs as a fraction of household income. The fourth term has random and fixed coefficients for several other vehicle characteristics interacted with household demographics. The second-to-last term, δ_{jt}, is a fixed effect for vehicle j in market t that absorbs effects that any vehicle characteristic has on utility that is invariant across households.

Households can buy one of J new vehicles or they can opt for the outside option, $j = 0$. A household opting for the outside option (also known as the outside good) can be thought of as the household buying a used car or not making a vehicle purchase during the sample year. This outside option serves two purposes. First, it allows me to directly use the estimated parameters for computing welfare effects of automobile policies. Second, it allows me to estimate the distribution of consumer valuation of fuel economy for a more representative sample of households.[12] In line with common practice, I normalize the utility of the outside good to be zero [113].

I assume that households choose the alternative that yields the highest utility. That is household i chooses car j in vehicle t if

$$U_{ijt} > U_{ikt} \text{ for all } k \neq j. \tag{2.3}$$

[12]Restricting the model to be conditional on buying a new car would provide estimates for WTP for consumers that bought a new car in the sample period, which is not representative of the entire U.S. population. In fact, in the sample that I use from the 2009 NHTS data, the average income of households that bought a new car was about \$ 76,000 while the average income of households in the entire sample was about \$ 58,000.

The probability that household i chooses vehicle j in market t is then

$$\begin{aligned}
P_{ijt} &= Prob(U_{ijt} > U_{ikt} \text{ for all } k \neq j) \\
&= Prob(V_{ijt} + \varepsilon_{ijt} > V_{ikt} + \varepsilon_{ikt} \text{ for all } k \neq j) \\
&= Prob(\varepsilon_{ikt} - \varepsilon_{ijt} < V_{ijt} - V_{ikt} + \text{ for all } k \neq j).
\end{aligned} \tag{2.4}$$

I assume that the error components are drawn from a type 1 extreme value distribution. Conditional on preference parameters $\Omega = \left\{\alpha, \gamma, \beta_i, \theta_i, \delta_{jt}\right\}$, the choice probability is the standard logit expression

$$P_{ijt} = \frac{e^{V_{ijt}(\Omega)}}{\sum_k e^{V_{ikt}(\Omega)}}. \tag{2.5}$$

To obtain unconditional probabilities, we must integrate out Ω. Since some of the coefficients in Ω are random, there does not exist a closed-form solution for this integration. Instead we write the unconditional probability as an integral expression:

$$P_{ijt} = \int \left(\frac{e^{V_{ijt}(\Omega)}}{\sum_k e^{V_{ikt}(\Omega)}} \right) f(\Omega) d\Omega. \tag{2.6}$$

The function $f(\cdot)$ is the mixing distribution for the parameters in Ω.[13] Since there is no closed form solution for (2.6), I must simulate the probabilities.

I include a fixed effect for car j in market t (δ_{jt}) to deal with the standard problem of vehicle price endogeneity. The problem stems from the fact that there may be several vehicle attributes valued by consumers that are not observed by the researcher, such as sportiness or smoothness of ride. These attributes are

[13] For the parameters that do not vary randomly across households, the marginal mixing distribution is degenerate.

likely to command a price premium. If the researcher leaves these attributes out of the observed portion of utility, they will be subsumed into the error term ε_{ijt}. As a consequence, the error term will be correlated with price. Since most unobserved attributes are likely to be desirable, leaving them out of the observed portion of utility will depress the magnitude of the price coefficient, suggesting that consumers are not very sensitive to price changes. This problem is of first order concern in the context of estimating willingness-to-pay for an attribute.[14]

Including fixed effects in the model can alleviate the problem of price endogeniety. The fixed effect (also commonly called mean utility) of car j in market t will absorb any vehicle characteristics valued by households that are invariant across households. Once the fixed effects are estimated, they can be used in an instrumental variables framework where instruments for price are used. This step is generally called the second stage and was first introduced in [18] and [19]. Formally, the fixed effects are regressed on several observed vehicle characteristics, including price:

$$\delta_{ijt} = \lambda + \eta p_{jt} + \phi x_{it} + \epsilon_{it}. \tag{2.7}$$

The endogeneity of vehicle price p_{jt} is dealt with by instrumental variables.

[14] This is the case when there is a separate coefficient for price and other included attributes.

2.4 Data

I gather data from several sources to carry out the estimation of the model. For data on household demographics and vehicle purchases I use the National Household Transportation Survey (NHTS). This is a nationally representative survey that is run every five to eight years, with the most recent being completed in 2009.[15] The NHTS asks several dozen questions about household backgrounds, including annual income, the number of individuals currently residing the the household and the highest level of education achieved. It also asks detailed questions about household vehicle holdings and trip behavior, including the purchase month of each vehicle currently owned by the household and the make and model of each vehicle.

I estimate my model from a balanced sample drawn from the two most recent waves of the NHTS, 2001 and 2009. These waves include household information surveyed approximately one year prior to the publish date, so that the 2001 survey includes information from the year 2000 and the 2009 survey includes information from the year 2008. I use these waves for two reasons. First, current consumer preferences are likely to be similar to those from these points in time relative to older waves. Second, average gasoline prices during these points in time are quite different.[16] Large differences in gasoline prices provides substantial variation in the present value of fuel costs, which helps accurately pin down how consumers

[15] Previous NHTS surveys were conducted in 1969, 1977, 1983, 1990, 1995 and 2001.

[16] The average national gasoline price in 2000 was $ 1.46 per gallon. By 2006 the average gasoline price had topped 2.50 per gallon and by 2008 the price had reached $3.26 per gallon.

value fuel economy.

I lack data on MSA vehicle shares for 2008. Instead, I have data for 2006 shares. For this reason I use data from the 2009 survey for vehicle purchases in 2006. This can be done since survey respondents are asked to report the month and year of purchase for all of the vehicles that they currently own. To use the household data from the 2009 wave, however, I need to make an assumption. I assume that consumer demographics do not change from 2006 to 2008. This assumption may not be valid for some households, but for the average household it is probably accurate.

The NHTS does not directly inquire about household vehicle purchases but instead requests that respondents state when they purchased and the make and model of the vehicles that they own. With these data I can assign new vehicle purchase decisions to each household. For example for the 2009 survey, if the household reports having acquired a model-year 2006 vehicle in 2006, then I assign that household as buying the vehicle new.[17]

I link the household level data with market level data from R.L. Polk Company. These data include total vehicle sales of new vehicles purchased in years 2000 and 2008 for nine Metropolitan Statistical Areas, which are regions of the country that have relatively large populations and economic ties. In particular the geographic region for each MSA is based on the 1999 definition by the Office of Management

[17] This is a reasonable assumption since very few vehicles that are bought new are sold within one year of purchase.

and Budget.

There are several reasons for combining the NHTS data with the market share data. The first reason is that doing so allows me to more accurately estimate the second stage household invariant coefficients, including vehicle price. This is because every vehicle in each MSA is assigned a unique mean utility, which is then used to estimated the second stage.[18] The second reason is that incorporating the MSA data reduces sample variance. This is because the MSA data provides actual new vehicle shares, while the NHTS only provides sample shares.

In Table 2.1, I provide key statistics of the two datasets. There are 18 MSA (Year) pairs that I use for estimation. In Table 2.1, I report average and standard deviation of income, fraction of households purchasing a new vehicle, the average and standard deviation number of children and the proportion of the sample that has a college degree. There is substantial household demographics heterogeneity both across and within the MSAs. For example, 17 percent of households in Albany, NY from the 2000 survey are retired, while almost 30 percent are retired in Madison, WI. This variation is utiliized to accurately estimate the first stage of the model.

[18] An alternative would be to define markets as years instead of year-MSA pairs. This, however, would dramatically lower the number of observations in the second stage, which would lead to inaccurate estimation results.

Table 2.1: Household Demographics

MSA	Year	Pct. w/ Children	Pct. Retired	Pct. w/ College[a]	Size[b]
Albany, NY	2000	43	17	34	2.62
De Moines, IA	2000	37	21	34	2.43
Houston, TX	2000	30	23	38	2.42
Lancaster, PA	2000	33	21	34	2.37
Madison, WI	2000	34	29	45	2.47
Miami, FL	2000	40	23	44	2.52
Milwaukee, WI	2000	42	17	43	2.68
Nashville, TN	2000	34	23	31	2.44
Phoenix, AZ	2000	38	23	46	2.48
Albany, NY	2006	26	39	54	2.29
De Moines, IA	2006	31	31	54	2.45
Houston, TX	2006	26	41	57	2.46
Lancaster, PA	2006	30	34	48	2.42
Madison, WI	2006	24	43	49	2.26
Miami, FL	2006	31	41	54	2.37
Milwaukee, WI	2006	26	39	54	2.29
Nashville, TN	2006	31	31	54	2.45
Phoenix, AZ	2006	26	41	57	2.46

[a] Pct. w/ College denotes the percentage of households that have at least one individual with a college degree.

[b] Size denotes the average total number of individuals living in the surveyed household.

Another source of data that I use are annual issues of Automotive News Market Data Book, which include vehicle characteristics. The characteristics are price (measured in the manufacturer's suggested retail price, MSRP), footprint, miles per gallon (MPG), vehicle class (car, van, SUV, truck), and vehicle segment.[19]

2.4.1 The Present Value of Fuel Costs

An important variable that I must construct for each vehicle is a measure of fuel costs over the lifetime of the vehicle. Formally this variable for household i owning vehicle j in market t is given by

$$fc_{ijt} = \mathbb{E}\left[\sum_{y=1}^{Y_j} \frac{VMT_{ijty} gp_{ity} GPM_{jt}}{(1+\delta_i)^{Y_j}}\right], \tag{2.8}$$

In the summation bounds of (2.8) y denotes a future year and Y is vehicle lifetime of car j. The term VMT_{ijty} is vehicle miles traveled by household i in vehicle j in market t in year y. Gasoline prices faced by household i in future year y are gp_{ity} and the inverse measure of fuel efficiency gallons per mile for car j in market t is denoted by GPM_{jt}. Finally household i's private discount rate is δ_i. The numerator of the fraction within the summation measures the expected gasoline cost of one year of travel by household i owning vehicle j in market t. This term is divided by a discount factor $\frac{1}{(1+\delta_i)^{Y_j}}$ to convert the cost to present value. The yearly costs are then summed across the expected lifetime of the vehicle. The expectation operator

[19] Ideally I would use transaction prices in the estimation. These data, however, are not available through the NHTS. Furthermore, I would need hypothetical transaction prices for vehicles that each household did not buy, which would be difficult (if not impossible) to construct.

in the front of the summation is present because these costs come after the vehicle is bought during use in future years.

Vehicle miles traveled and vehicle lifetimes

To estimate vehicle miles traveled and vehicle lifetimes, I use a meta-analysis by [83].[20] The data reported in this report are used by the NHTSA to assess the effects of proposed fuel economy and safety standards. The file reports average yearly weighted VMT separately for cars and light trucks. Weighted average yearly travel is the product of vehicle survivability and VMT schedules. For example, for a 10-year-old passenger car, the estimated survivability of the car is 79 percent and the estimated VMT is 11,193 (Table 7 in [83]). Therefore the weighted average travel miles during the 10th year of the car's lifetime is $0.79 * 11,193 = 8,804$. Data on estimated VMT is derived from the 2001 NHTS while survivability is obtained from a 1977 to 2002 window of data from the National Vehicle Population Profile.[21]

I assume that expectations for VMT of cars and light trucks follow separate

[20]This is an updated version of an older 1995 report that uses similar methodology.

[21]In using these values to calculate annual VMT, I am implicitly assuming that VMT is exogenous and independent of fuel costs. This may appear as an unrealistic assumption since the choice of vehicle and annual VMT are typically considered to be jointly chosen by households [12]. [51] finds, however, that estimating elasticity of new vehicle fuel economy with respect to gasoline prices is not sensitive to the independence assumption. (He finds that the average elasticity of new vehicle fuel economy is 0.09 both with and without the assumption.) [5] is another paper that suggests that the independence assumption will not have a significant impact on household WTP. They find that find that making VMT endogenous in the vehicle purchase decision has little impact on the mean WTP for reducing fuel costs. Moreover, since I am using household demographics data, I am able to capture household heterogeneity in expected VMT through demographics and vehicle characteristics interaction terms.

schedules since these vehicle types are generally have different purposes.[22] In line with [83] I assume that passenger cars last 25 years and that trucks last 36 years (Tables 7 and 8 in [83]). The schedules show that both passenger cars and light trucks are driven heavily during their early years of life. During the first year of operation, the average car is driven $14,231$ miles. By the 15th year, estimated VMT drops to $9,249$. Vehicle survivability follows a similar pattern. The probability that a car or light truck remains on the road after the initial years of life is near 100 percent. Light truck survivability remains above 90 percent for the first four years, while passenger car survivability remains above 90 percent for the first six years. As cars age their survivability rapidly drops. By the 20th year of life, a passenger car's probability of remaining on the road has dropped to below 10 percent.

Expected Gasoline Prices

I assume that households form expectations of gasoline prices based on current prices of their MSA. More specifically I assume that households expect that future gasoline prices equal current gasoline prices, which is consistent with recent survey evidence [6].

I collect annual average gasoline price data from the American Chamber of Commerce Research Association (ACCRA) database. For the two time periods I use for estimation there is substantial variation in gasoline prices across MSAs. Table 2.2 displays gasoline prices across the 18 MSA-year pairs. In general, gasoline prices are about one dollar higher in the MSAs for the 2006 data. This

[22] The exact schedules that I use appear in Tables 7 and 8 in [83].

increase is attributed to increased demand for crude oil and gasoline and steady supply.[23] Even within the same year, however, there is substantial variation across MSAs. For example, the gasoline price in Albany, New York in 2000 is $ 1.58 per gallon. The price per gallon of gas in the same year in Nashville, Tennessee is $ 2.11.

[23]The increase in demand for oil comes primarily from surging economies during the time period, including China and India.

Table 2.2: Household Fuel Costs

MSA	Year	Average Gasoline Price	Present Value Fuel Cost[a] Mean	Std.
Albany, NY	2000	1.58	9,028.75	2,294.72
De Moines, IA	2000	1.69	9,671.74	2,458.15
Houston, TX	2000	1.79	9,671.37	2,601.14
Lancaster, PA	2000	1.70	9,718.63	2,470.06
Madison, WI	2000	1.72	9,819.10	2,495.60
Miami, FL	2000	1.63	9,343.55	2,374.73
Milwaukee, WI	2000	2.02	11,573.94	2,941.60
Nashville, TN	2000	2.11	12,089.68	3,072.68
Phoenix, AZ	2000	1.82	10,401.81	2,643.70
Albany, NY	2006	2.52	14,605.23	3,659.45
De Moines, IA	2006	2.49	14,443.02	3,618.81
Houston, TX	2006	2.64	15,288.86	3,830.74
Lancaster, PA	2006	2.59	15,022.36	3,763.97
Madison, WI	2006	2.51	14,524.13	3,639.13
Miami, FL	2006	2.40	13,910.02	3,485.26
Milwaukee, WI	2006	2.85	16,511.27	4,137.03
Nashville, TN	2006	2.87	16,603.97	4,160.25
Phoenix, AZ	2006	2.70	15,642.26	3,919.29

[a] A 5 percent discount rate is used to discount future annual costs to the present period. The present value of fuel cost is reported in 2006 dollars.

Gallons per mile

I collect miles per gallon (MPG) data for each vehicle from the fuel economy database organized by the Environmental Protection Agency (EPA). I combine city and highway fuel efficiency following the weighted harmonic mean formula given by the EPA to measure MPG of a car: $\text{MPG}_{jt} = 1/[(0.55/\text{city MPG}_{jt}) + (0.45/\text{highway MPG}_{jt})]$.[24] Among the 2006 new vehicles, the average MPG is 23.5. The vehicle with the lowest MPG in 2006 is Dodge Ram which can drive 14.63 miles on a single gallon of gas. At the other extreme the most fuel efficient new 2006 vehicle is the Honda Insight which gets 56.54 miles per gallon. I convert MPG of each vehicle into gallons per mile by taking the inverse: $\text{GPM}_{jt} = 1/\text{MPG}_{jt}$.

Discount rate

The final term to calibrate in (2.8) is household i's discount rate. This rate represents household i's intertemporal opportunity cost of money. In the context of this paper, this rate represents the rate at which future gasoline costs are discounted to the present. For households whose marginal dollar comes from an auto loan, this rate is equal to the lowest interest rate that the household can get. For households whose marginal dollar comes from investment, this rate is equal to the market rate of return on equity.

I assume that households have a discount rate of five percent. This assumption is slightly lower than the 6 percent discount rate assumed in [5] who base their

[24]The EPA adjusts their test measures down by about 15 percent to reflect road conditions. I use the adjusted EPA adjusted values.

calibration on two sources: 2001, 2004 and 2007 Surveys of Consumer Finances (SCF) and the average real return on the S&P 500 between 1945 and 2008. Allcott and Wozny [5] assign a rate based on the average real interest rate for used vehicle loans, which is 6.9 percent. On average the real interest rate for new vehicle loans is about one percent lower than the rate for used cars. Therefore I assume that the average household discounts future fuel costs by 5 percent. The assumption of a 5 percent discount rate is within the range of rates used in analyses of major transportation sector policies by the NHTSA, including the most recent adjustment of CAFE standards [96].[25]

Summary

Table 2.3 summarizes the key assumptions made to construct the present value of fuel costs for each household in each market.

[25]The NHTSA Final Regulatory Impact Analysis of CAFE reports cost estimates with a 3 percent and 7 percent discount rate.

Table 2.3: Assumptions for Computing the Present Value of Fuel Costs

Variable	Value	Sources
Vehicle miles traveled	Age and class dependent[a]	[83]
Vehicle lifetime	25 years for cars 36 years for light trucks	[83]
Gallons per mile	Model and year dependent[b]	Environmental Protection Agency[c]
Gasoline price	MSA and year dependent[d]	ACCRA Database
Discount rate	5 %	[5] 2001 and 2007 ACF Survey

[a] Passenger cars and light trucks have separate lifetime vehicle miles traveled schedules. Each schedule is calculated by taking the product of the expected vehicle miles traveled of the vehicle at a given age and the probability of the vehicle remaining in the fleet at a given age. Both expected vehicle miles traveled and the survival probability drop as the vehicle ages.

[b] Both waves of data that I use contain many of the same vehicle models, such as the Honda Accord. The vehicle attributes, including gallons per mile, of vehicle models may be different between the two waves since manufacturers make modifications across generations of vehicles (which generally last about five years). For example, the 2000 version of the Honda Accord gets 27.03 MPG while the 2006 version gets 27.66 MPG.

[c] The EPA adjusts their recorded laboratory fuel efficiency down by about 15 percent to reflect road conditions. I use the adjusted EPA adjusted values.

[d] See Table 2.2 to view the substantial variation in gasoline prices across MSAs and across year.

One potential criticism of my approach is that consumers may be heterogeneous in the values that I have chosen. For example, some consumers may have different expected driving habits over the course of the vehicle's life.[26] My behavioral model is robust to this possibility because I allow household preferences for fuel cost reductions to vary randomly across the population. Therefore, if there are differences in driving habits, this will be reflected in some as heterogeneity the in the valuation of fuel cost reductions.[27]

Table 2.2 summarizes mean and standard deviations of lifetime fuel costs for vehicles available in each of the 18 MSA-years. The statistics illustrate that there is substantial variation in fuel costs across vehicles within the same year and across years. This is primarily due to the large variation in gasoline prices.

The overall magnitude of lifetime fuel costs are nontrivial relative to vehicle purchase prices. As Table 2.2 illustrates, lifetime fuel costs are around $10,000$ dollars, which is between one-half and one-third of a typical new vehicle bought in 2006. This implies that there is a large incentive for households to correctly value fuel economy when making a vehicle purchase decision. It also implies that there is potential for large welfare losses from market failures related to how households value energy efficiency.

[26]Two additional criticisms of my approach include endogenous usage decisions and resale decision. Consumers buying a more fuel efficient vehicle are likely to drive their purchased car more. Furthermore some consumers may decide that they want to sell their vehicle before the vehicle is scrapped. In his appendix [5] show analytically that my assumptions should be robust to these possibilities.

[27]Consumers that expect to drive more will have a larger (in magnitude) coefficient for fuel cost reductions.

2.5 Estimation

I estimate the parameters of the random utility model in two stages. In the first stage I estimate parameters of the model that vary across households. This stage requires simulating the probabilities specified in (2.6) since mixed logit does not have closed form solutions for choice probabilities. In the second stage I estimate preference parameters for vehicle characteristics that are invariant across households. In this stage I instrument for vehicle prices using instrumental variables.

2.5.1 Estimation Details: First Stage

In the first stage I estimate parameters that vary across households using maximum simulated likelihood. The simulated log likelihood function is

$$SLL = \sum_t \sum_i \ln P_{ij^*t}, \tag{2.9}$$

where P_{ij^*t} represents the predicted probability that household i buys car j^* in market t. Vehicle j^* represents the vehicle actually chosen by household i.

I allow three parameters to vary randomly across households: the present value of vehicle fuel cost relative to income (β_i), vehicle footprint and a constant. I assume that the mixing distribution for vehicle footprint and the constant are normal since there is no apriori reason to believe that the signs of these parameters should be restricted. The sign for vehicle fuel cost, however, should be negative, holding other vehicle attributes constant. For this reason I assume that the mixing distribution for the present value of vehicle fuel cost is truncated normal, censored at zero and restricted to be negative. This allows the distribution for the present value of fuel cost to have a point mass at zero, representing a share of the population that ignores or is inattentive to fuel costs. This assumption turns out to be especially crucial when evaluating the distribution of willingness-to-pay for reducing fuel costs.

I must simulate the probabilities in (2.6) to evaluate the simulated log likelihood. To speed up the estimation routine I use Halton sequences to simulate the probabilities [113]. For each household I use 200 Halton draws.[28]

One difficulty in the first stage estimation is obtaining the mean utilities δ_{jt}. The difficulty arises because in each wave of the data there are over 200 new vehicles available for purchase. As a result I must estimate at least 200 fixed effects (one per vehicle). Adding 200 parameters to the model makes estimation computationally infeasible. Before describing how I estimate these fixed effects, I describe an alternative. One alternative is to aggregate the vehicles into groups, such as vehicle classes as in [12]. This alternative is undesirable in my context because there is substantial variation in fuel efficiency within class. Aggregating masks this variation, which would lead to biased estimates for willingness-to-pay.

[28] [113] suggests that Halton draws are much more efficient at simulating probabilities of mixed logit models. An alternative to Halton draws are quadrature methods [20].

To estimate the mean utilities I follow [19]. This approach provides a method for obtaining by using a moment condition that predicted vehicle shares in a given market equal observed market shares. Denoting $\boldsymbol{\delta} = \left\{\delta_{jt}\right\}$ as the set of mean utilities and S_{jt} and $\hat{S}_{jt}$ as observed market share and predicted market share for alternative j in market t, respectively, the moment conditions are

$$S_{jt} = \hat{S}_{jt}(\Omega, \boldsymbol{\delta}^h) \text{ for all } j, t, \tag{2.10}$$

where Ω is a vector of first stage parameters. [18] shows that there exists a unique set of mean utilities that satisfy (2.10). Since (2.10) is non-linear in $\boldsymbol{\delta}$, the mean utilities cannot be obtained analytically. Barry et al. suggest using a difference equation, known as "the contraction," which maps an initial value for the vehicle j market t fixed effect to a new value:

$$\delta_{jt}^{h+1} = \delta_{jt}^{h} + \ln(S_{jt}) - \ln(\hat{S}_{jt}(\Omega, \boldsymbol{\delta}^h(\Omega))) \text{ for all } j, t. \tag{2.11}$$

Berry et al. proved that (2.11) is a contraction mapping, which implies that for any initial delta $\boldsymbol{\delta}^h$, the mapping will converge to a unique delta that satisfies (2.10). In all estimation routines that invoke the BLP method, the iteration of the difference equation (2.11) occurs within the overall optimization. More specifically, at each search value for the parameter vector Ω, the mapping (2.11) is iterated until the difference between δ_{jt}^{h+1} and δ_{jt}^{h} are sufficiently close.[29]

A standard concern with this approach is that it is computationally expensive and therefore takes a substantial amount of time to perform the estimation. I

[29] The concensus on the tolerance level for the maximum difference between successive iterations of $\boldsymbol{\delta}$ is that it should be set to be no larger than $1e-14$.

adopt an alternative form of the contraction mapping that is based on Newton's method to speed up the estimation routine [80].[30]

In the first stage I include several household demographics and vehicle characteristics interaction terms to model additional observed household heterogeneity.[31] The household demographics variables include income, whether the household has children (modeled with a dummy variable), household size, whether the head of the household is retired (modeled with a dummy variable), whether the head of the household has a college degree (modeled with a dummy variable), and annual trip miles for all vehicles owned by the household. The vehicle attributes include price, a set of dummy variables for type (car, van, SUV or pick up), footprint, weight, and origin (US or Asian).

[30] I use the following difference equation to obtain the mean utilities:

$$\delta_{jt}^{h+1} = \delta_{jt}^{h} + \left[\frac{\partial \ln(\hat{S}_{jt}(\boldsymbol{\theta}, \boldsymbol{\delta}^{h}(\boldsymbol{\theta})))}{\partial \boldsymbol{\delta}^{h}}\right]^{-1} \left[\ln(S_{jt}) - \ln(\hat{S}_{jt}(\boldsymbol{\theta}, \boldsymbol{\delta}^{h}(\boldsymbol{\theta})))\right] \quad \text{for all} \quad j, t.$$

Notice that this difference equation is almost identical to the original contraction mapping in [19]. My method multiplies the difference in log shares by the Jacobian of the log moment conditions (2.10), which (put simply) provides the mapping with a more direct search path. This alternative method converges to the same set of fixed effects as (2.11) but typically takes about one-fourth as long to estimate. See [80] for more details.

[31] Incorporating consumer heterogeneity has two benefits. First, it allows the researcher to provide a more realistic model of household decision making in contexts where households are likely to have substantially different tastes, which is expected in the case of automobiles. Second, it allows the researcher to explore welfare effects for different groups of consumers, which can be relevant for policy analysis. For example, Jacobsen (2013) finds that CAFE standards significantly affect low-income households and that this effect changes across time.

2.5.2 Estimation Details: Second Stage

With the mean utilities estimated from the first stage I can identify the effect of vehicle characteristics that are invariant across households on household utility. I regress the mean utilities on several vehicle characteristics, including vehicle price (deflated to year 2000 dollars), the log of horsepower, the log of weight, the log of footprint, an indicator variable for hybrids, segment dummy variables (e.g. mid-size, compact, etc.) and vehicle type dummy variables (e.g. car, truck etc.).

I use several instruments for vehicle price. Before I discuss each instrument, it is useful to note the criteria for an instrument to be valid in the context of this model. A valid instrument should not be correlated with unobserved vehicle characteristics that are correlated with price, should be correlated with price and should only influence mean utility indirectly through price. The three instruments that I use that intuitively satisfy these conditions include the price of aluminum interacted with vehicle type, the price of steel interacted with vehicle type and the sum of gasoline taxes and crude oil prices.

There is little reason to believe that aluminum and steel prices are correlated with how consumers value unobserved characteristics like smoothness of ride. Furthermore, consumers do not directly value aluminum and steel prices, but instead value the price of a vehicle. Finally, aluminum and steel prices are likely to be correlated with vehicle prices since these metals constitute a significant fraction of the total mass of a vehicle.

Gasoline taxes and crude oil prices are also likely to satisfy the three valid instrument conditions. As long as some consumers value fuel economy, higher gasoline taxes and crude oil prices will cause the equilibrium relative price of high MPG vehicles to rise [28]. Moreover, consumers are unlikely to directly value taxes or crude oil prices, and these components are unlikely to be correlated with unobserved product attributes.

2.5.3 Estimation Details: Implied Distribution of WTP for Reducing Fuel Costs

The WTP for reducing one dollar of the present value of fuel costs can be calculated based on the estimation results from the first and second stages. In discrete choice models, WTP for an attribute is equal to the division of two values: the marginal utility of the attribute divided by the marginal utility of price.[32] Since I specify fuel cost as a random coefficient, the marginal utility of fuel costs will be a distribution. As such, I need to simulate the distribution for WTP for

[32]The intuition for this calculation is best understood with an example. Suppose a household has preferences for fuel costs and price such that their marginal utility for fuel costs is -10 utils per dollar and their marginal utility for price is -15 utils per dollar. This means that the household experiences 10 more utils whenever fuel costs are one dollar lower. In other words, if a household buys a fuel efficient car that saves them one dollar of fuel costs, they experience 10 more utils. How much more would the household be willing to pay for this fuel efficient car? They will not be willing to pay one dollar more in the up-front purchase price, since that would cause the household to experience losing 15 utils. Instead the household would be willing to pay up to 10/15 = 0.67 dollars as this is the value that would make the household indifferent. In other words, if the household had to pay 0.67 more in the up-front price to save one dollar of fuel costs, their change in utility would be +10 utils/dollar*(one dollar) -15 utils/dollar*(0.67 dollars) = 10 utils - 10 utils = 0 utils.

reducing fuel costs. I do so by calculating WTP at each draw that is assigned to a household, computing the distribution for WTP across all households and saving this distribution. I then average the distributions across the 200 draws.

2.5.4 Estimation Results: First Stage

In Tables 2.4 and 2.5, I present the estimation results for the first stage.

Table 2.4: First Stage Estimation Results – Random Coefficients

Parameter	Estimate
Fuel Cost/Income mean	-3.13** (1.32)
Fuel Cost/Income standard deviation	6.42** (2.85)
Log(footprint) standard deviation	5.33** (2.53)
Constant standard deviation	9.78*** (2.92)

Standard errors are reported in parenthesis. ** denotes significance at the 5 percent level. *** denotes significance at the 1 percent level.

Table 2.5: First Stage Estimation Results – Fixed Coefficients

(a) Household Characteristics Parameter	Estimate	(b) Interactions Parameter	Estimate
1/Income	-18.56*** (6.74)	Price/Income	-0.52** (0.21)
Children Dummy	-0.49 (0.75)	Children Dummy*Car Dummy	-6.17** (3.08)
		Children Dummy*Van Dummy	-4.97** (2.05)
		Children Dummy*SUV Dummy	-5.35** (2.22)
		Children Dummy*Pickup Dummy	-6.18* (3.16)
Household size	-4.30 (3.96)	Household Size*Footprint	0.84** (0.42)
Retirement Dummy	-4.80 (5.51)	Retired Dummy*Weight	0.08 (0.60)
College Degree	2.38 (3.01)	College Degree*Domestic[a]	0.16 (0.32)
		College Degree*Asian	0.67** (0.33)
Trip Miles	3.15 (4.13)	Trip Miles*Footprint	0.23 (0.52)

Standard errors are reported in parentheses. * denotes significance at the 10 percent level. ** denotes significance at the 5 percent level. *** denotes significance at the 1 percent level.

Table 2.4 shows mean and standard deviation for the fuel cost as a fraction of income parameter and standard deviation estimates for the remaining random parameters. The parameters are significant at the 5 percent level and have expected signs. The fuel cost relative to income mean and standard deviation provide a glimpse of the underlying distribution for willingness-to-pay for reducing fuel costs. The mean has a negative sign, which intuitively suggests that the average consumer dislikes fuel cost. The standard deviation, however, is more than twice as large as the mean. This suggests that there exists substantial heterogeneity in how consumers value fuel costs. This suggests that there may be large differences in how households value fuel economy. Without the second stage parameters, however, we cannot conclude whether this significant dispersion leads to significant heterogeneity in WTP since WTP is a function of the marginal utility of price as well as the marginal utility of fuel cost.

Table 2.5 shows the coefficient estimates for household demographics and interaction terms. The significance of these effects is not as strong as the random coefficients as several parameters are not significantly different from zero. The signs of the most of the coefficients, however, follow common intuition. The inverse of income enters with a negative sign, suggesting that consumers with high income are more likely to buy a new car. The coefficient on price as a fraction of income is negative and significant, implying that consumers with the same income dislike higher priced vehicles, holding other vehicle attributes constant. Households that drive more are more likely to purchase a new car, although this effect is not statistically significant.

2.5.5 Estimation Results: Second Stage

In Table 2.6, I report the coefficient estimates from the second stage. I report two sets of estimates. The first column "OLS Estimates" includes estimates for a model where I do not instrument for vehicle price. The second column "IV Estimates" includes results from instrumental variables estimation where I instrument for price. The dependent variable in both sets of estimates is the mean utility for vehicle j in market t.

Table 2.6: Second Stage Estimation Results

Parameter	OLS Estimate	IV Estimate
Price	-0.26*** (0.03)	-0.57*** (0.06)
Log(Horsepower)	0.84*** (0.14)	1.34*** (0.18)
Log(Weight)	-1.94*** (0.35)	-0.98** (0.43)
Log(Footprint)	-7.26*** (0.44)	-7.36*** (0.46)
Hybrid Dummy	-1.62*** (0.14)	-1.57*** (0.17)
Constant	-1.30 (2.96)	-9.73*** (3.50)

Standard errors are reported in parentheses. * denotes significance at the 10 percent level. ** denotes significance at the 5 percent level. *** denotes significance at the 1 percent level.

I estimate both models with 3,951 observations.[33] Focusing on the OLS estimates, we find that the signs of the vehicle attribute coefficients make intuitive sense. Price has a negative and highly significant coefficient, suggesting that consumers favor vehicles that cost less to buy. The natural logarithm of vehicle horsepower is positive and significant at the one percent level, implying that consumers desire vehicles with more power and acceleration. Consumers dislike vehicles that are larger but have the same horsepower as the log of weight and footprint (which is defined as the product of the distance between a vehicle's tires and the vehicle's length) have negative coefficients.

When I instrument for vehicle price, coefficient signs and significance levels remain stable. The coefficient for price, however, becomes much larger in magnitude. This is an intuitive and common result in the discrete choice transportation literature beginning with the seminal article [19]. Unobserved vehicle characteristics, such as smoothness of ride, are likely to be positively correlated with vehicle price. When these characteristics are left out of the model, the coefficient on vehicle price will be biased up toward zero. This is exactly the effect we see when comparing the OLS results to the IV results. When I instrument for price, the coefficient doubles in magnitude, suggesting that consumers are much more sensitive to price than what is indicated by the OLS model. This is an important result because getting the correct magnitude for price is crucial

[33] In the 2000 wave, there are 203 unique vehicles across nine MSAs for a total of 1,827 unique vehicle-market observations. In the 2009 wave, there are 236 unique vehicles across nine MSAs for a total of 2,124 unique vehicle-market observations. Together, this gives a total of 3,951 unique vehicle-market observations.

for obtaining an accurate estimate of WTP which is a function of the marginal utility of price. For this reason, I use the estimates from the instrumental variables estimation to derive the WTP for reducing fuel costs.

2.5.6 Implied Distribution of WTP for Reducing Fuel Costs

The implied distribution of WTP for reducing fuel costs by one dollar is obtained by dividing the marginal utility of fuel cost by the marginal utility of price. Since fuel cost enters as a random coefficient, I must simulate the marginal utility of fuel cost. A histogram of the resulting distribution for WTP appears in Figure 2.1. The vertical red line denotes the mean of the distribution, which is at 0.98. The mean implies that the average willingness-to-pay to reduce fuel costs by one dollar is 98 cents. This suggests that the average household equally weighs the up-front purchase price of a car and the present value of fuel costs over the lifetime of the vehicle. This is consistent with several recent estimates of the WTP for reduced gasoline costs. Busse et al. [28] find that 100 percent of gasoline price changes between 1999 and 2008 are reflected in new and use car prices, suggesting that consumers correctly value the fuel cost savings of more efficient vehicles. On the other hand, Allcott and Wozny [5] find that over the same time period consumers appear to value one dollar of reduced fuel costs at only 76 cents, implying that consumers on average undervalue energy savings. They find, however, that this undervaluation almost disappears for newer vehicles. The authors provide separate WTP estimates for different age classes and find that fuel efficiency is valued more in newer vehicles.[34] For used vehicles that are less than three years old, the authors find that consumers value one dollar of reduced fuel costs at 93 cents, an estimate that is not statistically different than full valuation.

Figure 2.1 also reveals that there is substantial heterogeneity in how households value fuel efficiency. About 31 percent of households appear to be inattentive to or ignoring fuel costs, represented by a point mass of WTP at zero. Furthermore, many households appear to be over-valuing fuel costs as the histogram shows a significant mass above one. For convenience I summarize the distribution in Table 2.7. These results are broadly consistent with the heterogeneity estimated in [104]. In each of our studies we find that households appear to be very different with respect to how they value fuel costs when making new vehicle purchases. In contrast to [104], however, I find that a large fraction of households appear to ignore fuel cost as a vehicle attribute when buying a new car. This result will prove to be exceptionally relevant when discussing the potential explanations of the consumer heterogeneity.

[34]For very old vehicles (11+ years), WTP is only 26 cents. WTP monotonically rises as vehicle age declines.

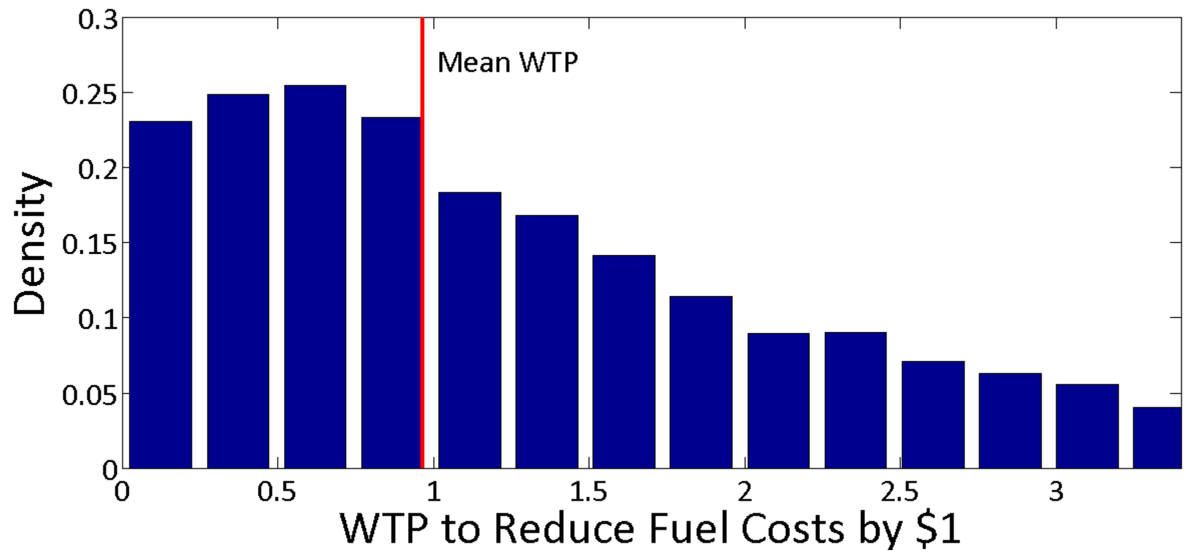

Figure 2.1: Implied Distribution of Willingness-to-pay for Reducing Fuel Costs by One Dollar

Table 2.7: Descriptive Statistics for WTP Distribution

Statistic	Value
Mean	0.98
Standard Deviation	1.15
Percent = 0	31
Percent Between 0 and 0.75	25
Percent Between 0.75 and 1.5	18
Percent Above 1.5	26

The resulting distribution for the WTP to reduce fuel costs by one dollar is a truncated normal that is censored at zero so that no households have an unrealistic negative WTP.

2.5.7 Discussion

What market failures or behavioral biases can explain the distribution for WTP in Figure 2.1? Several recent studies provide a host of possible explanations. One reason why households may appear to undervalue energy efficiency is time inconsistency. A household that is time inconsistent under-weights future periods when making a decision in the present. This distorts a household's decision to buy a durable good like a car since vehicles have operating costs at are incurred over the lifetime of the vehicle. Heutel [66] argues that time-inconsistency in the form of quasi-hyperbolic discounting can cause consumers to undervalue energy savings from fuel efficient vehicles.[35] Quasi-hyperbolic discounting is generally associated with beta-delta preferences, where a household's present view of the stream of utility from purchasing a product is $U = u_1 + \beta \sum_{t=2}^{T} \delta^t u_t$. The components of utility include instantaneous utility in period t, u_t, a discount factor, $\delta < 1$, and a measure of present bias, $\beta < 1$.[36] Although there does not exist empirical evidence supporting the notion that consumers are time-consistent when they make vehicle purchases, evidence does exist in other settings. For example, Laibson et al. [78] estimate parameters of a quasi-hyperbolic discounting model with data on US household savings and consumption choices. They find that $\beta = 0.7$ and $\delta = 0.96$, which is analogous to moderate undervaluation.[37]

[35][66] finds that if consumers are hyperbolic discounters, it is efficient to provide a fuel efficient vehicle subsidy (or an equivalent instrument) to correct the present bias.

[36]When $\beta = 1$ there is no present bias and preferences have the standard exponential discounting form.

[37]Laboratory evidence suggests a similar magnitude for present bias where β has been found to range between 0.6 and 0.7 [25].

Another related reason for undervaluation is temptation and self control. Tsvetanov and Segerson [115] argue that temptation may explain some of the energy efficiency gap. Their argument rests on the notion that consumers feel a real welfare cost when they must exercise self-control when making a purchase decision. If a consumer chooses between two alternatives where one of the options requires a high level of self-control, the consumer may be tempted and find it optimal to avoid the self-control cost and splurge. Energy efficient alternatives usually have higher purchase prices, so that consumers may be need to exert self-control to buy these goods instead of their cheaper energy inefficient counterparts.[38] If self control costs are high for some of the consumers, these consumers may find it to be privately optimal to undervalue or completely ignore the energy cost characteristic when making a purchase decision.

Credit constraints may explain the mass of consumers that appear to ignore energy costs. Since vehicles with higher fuel economy command higher prices (after controlling for other relevant vehicle characteristics), this would suggest that some low income households cannot afford to buy high MPG cars when they want to. This would bias down their valuation of WTP for reducing fuel costs.

Although credit constraints may have an impact on household WTP for fuel costs, I argue that this impact is small or non-existent in my model. One

[38] [115] consider a model of self control where an energy inefficient alternative has no self-control cost and where an energy efficient alternative has a positive self-control cost. Their focus is not on arguing how their model can explain recent estimates of the energy efficiency gap but instead works through a detailed instrument choice analysis where they compare the efficiency of usage taxes, efficiency standards and price taxes/subsidies.

reason that credit constraints may not be relevant in my context is because I am estimating WTP on new vehicle data. Households that purchase new cars generally have higher incomes and are less financially constrained.[39] A second reason is that I have estimated the model on a sub-sample of households that have annual incomes above $100,000$ dollars and I find that while the mass of households that appear to be inattentive to fuel costs falls, it only slightly falls.[40]

Testing which of the explanations is most likely to explain the distribution for WTP is out of the scope of this paper. Instead, I argue that there exists a simple and intuitive model that can rationalize the preferences that I estimate. A model of *rational inattention* can explain why a significant portion of the sample appear to ignore fuel costs. Sallee [101] formulates a model of rational inattention in the context of a consumer making a discrete choice among several energy intensive durable goods. The basic idea of the model is that consumers may face a decision to first gather and process information relating to the energy costs of each alternative before making a purchase choice. This information acquisition allows the consumer to make an ex-post optimal decision. For some, however, gathering and processing information may be exceptionally costly. As a consequence, some may find it ex-ante optimal to forego this step and ignore the energy cost attribute when buying a good. In the context of the estimation results presented in the

[39]The average annual income of households that purchase a new vehicle is about $88,000$ dollars. A related reason is that I am estimating an unconditional vehicle choice model, so that households have the choice of not purchasing a vehicle. In the sample that I use for estimation, about 87 percent of households do not buy a new car. Most households that are credit constrained are unlikely to receive a loan to buy any new vehicle. These households are unlikely to influence the estimated distribution for WTP.

[40]With this sub-sample 25 percent of households have a WTP to reduce fuel costs of zero.

previous section, around 31 percent of households appear to avoid gathering and processing information about energy costs while the remaining 69 percent make some effort and have a non-zero value on fuel costs.

A key appeal of this explanation is that is does not require the application of behavioral anomalies that are inconsistent with welfare maximization.[41] All the households in my sample – including the 31 percent of households ignoring fuel costs – make an ex-ante privately optimal decision. Moreover, rational inattention is exceptionally applicable to the choice setting of this paper which has many alternatives and many valuable characteristics for each alternative. This is the case because information gathering and processing is likely increasing in the number of alternatives and characteristics. In each year of my data the new vehicle choice set is over 200 cars, and each vehicle has at least a dozen relevant characteristics. This suggests that information gathering and processing are non-trivial for consumers looking to make a car purchase. This hypothesis is consistent with recent survey evidence presented in [2], which suggests that about 40 percent of households do not think at all about fuel costs when deciding to buy a car.[42]

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[41]The model of temptation presented by [115] also does not require a new framework for evaluating welfare. Ultimately, the results that I present in the simulation portion of the paper, however, do not depend on which explanation I stand behind. All that is required is that the model can predict that some consumers choose to ignore future fuel costs when making a vehicle purchase decision but benefit if they are swayed to buy a more fuel efficient vehicle.

[42]The survey consisted of a representative sample of about 2,000 US households. The exact question asked to households was the following: "In this survey, we asked you to calculate fuel costs fairly mathematically and precisely. Think back to the time when you were deciding whether to purchase your vehicle. At that time, how precisely did you calculate the potential fuel costs for your vehicle and other vehicles you could have bought?" 40 percent of households responded with "I did not think about fuel costs at all when making my decision."

Thus far I have discussed likely candidate theories that explain the left side of the distribution in Figure 2.1. What about the right side, which includes consumers that appear to be overvaluing fuel economy? Overvaluation can emerge from two distinct sources that have different policy implications. The first source is that some households are green. Green households derive utility when buying a fuel efficient car that is independent of fuel cost savings. These consumers, then, appear to be willing to pay more than one dollar to reduce a fuel costs by a dollar.[43]

Another potential source is the MPG illusion. Several studies have documented that consumers systematically undervalue fuel cost savings when comparing two very low MPG cars (for example 14 MPG vs. 15 MPG) and systematically overvalue fuel cost savings when comparing two very high low MPG cars (for example 49 MPG vs. 50 MPG) [3, 79].[44] However, Allcott [3] shows that the MPG Illusion has a minimal impact on equilibrium market shares and a small effect on consumer welfare. Therefore, when I analyze the welfare effects of alternative policies, I assume that consumers with a WTP above one fully internalize any welfare changes from fuel cost savings.

[43]To the best of my knowledge there does not exist an empirical study asking whether environmentally conscious households have a WTP above a dollar. Since rigorously answering this question is out of the scope of the current paper I leave this specific question for future work.

[44]The MPG illusion to a slight extent can explain why some consumers undervalue fuel economy. It cannot explain, however, why some consumers appear to ignore fuel costs when buying a car.

2.6 Policy Analysis

The degree of heterogeneity in how households value fuel costs has relevant policy implications. If consumers are different in their degree of undervaluation, then policies aimed at reducing energy use are most efficient when they preferentially influence the purchase decisions of the share of the population that undervalues the most. An effective policy will primarily target households that are under-investing in energy efficiency while having little or no effect on the choices of households that fully value the cost savings from energy intensive durable goods. In the next section I simulate the welfare effects of three existing policies and distill the different channels of adjustment that interact with the heterogeneity in fuel cost valuation.

Thus far we have seen that while the average household values equally the upfront purchase price and the present value of fuel costs, there appear to be a significant fraction of potential buyers that are inattentive to fuel costs. As a consequence, for a policy to be efficient, it must be able to primarily target the subset of the population that is inattentive. This result begs for an answer to the following question: Which existing policies in the transportation sector effectively target these consumers?[45] To answer this question, I simulate the welfare effects of three current policies given my estimated distribution of WTP for reducing fuel costs. I evaluate the welfare effects of a gas guzzler tax, a feebate and

[45]An equally important pursuit is determining the optimal combination of policy instruments when faced with household undervaluation of fuel economy. I refer the reader to [4] for an analytical and simulation-based analysis of the optimal policy response to undervaluation.

a fuel efficient vehicle subsidy. These three policies represent a broad portion of the many initiatives in the transportation sector that are aimed at increasing fleet-wide fuel economy.

Another major policy in the transportation sector that increases fleet fuel economy is a gasoline tax. I do not evaluate the welfare effects of a gasoline tax for two reasons. First, doing so would require a detailed simulation model that would include several adjustments of household behavior that I do not estimate in my empirical model.[46] Including these important margins of adjustment would be computationally expensive and is out of the scope of this paper. Second, adjusting gasoline taxes is currently a politically infeasible instrument for increasing fuel economy. Third, the primary objective of a gasoline tax is to raise revenue, whereas the instruments that I consider have a primary objective of encouraging consumers to buy more fuel efficient cars.[47]

2.6.1 Assumptions

Since the simulation requires some notion on the supply of new vehicles and calculations of welfare, in this section I lay out assumptions of the simulation

[46] An important margin of adjustment is yearly vehicle miles traveled, which has been shown to play a pivotal role in evaluating the relative efficiency of gasoline taxes to fuel economy standards [70].

[47] A fourth reason is also revenue related. [12] demonstrate that the efficiency effects of gasoline taxes greatly depend on how the revenue generated from a gasoline tax is returned to households. To properly evaluate the effects of a gasoline tax would require following the steps taken in this paper, which would distract the analysis from comparing the relative effects are separate policies in the transportation sector. I leave this pursuit for future work.

model. I assume that supply of new vehicles is perfectly competitive. This is clearly a simplifying assumption of the new vehicle market, as many existing studies suggest that the supply side is imperfectly competitive [53, 54, 12]. I choose to make this assumption for three reasons. First, assuming perfect competition dramatically simplifies the analysis and focuses the effects on the consumer side of the market. Second, relaxing this assumption requires taking a stance on the information about consumer valuation of fuel economy that suppliers use to set prices and vehicle attributes. There exists limited empirical evidence regarding this issue.[48] Third, the policies that I consider are more easily comparable with the perfect competition assumption. This is because a fee or subsidy levied on a vehicle directly translates into an equilibrium price change for the vehicle that is exactly equal to the fee or subsidy.

Demand for new vehicles comes directly from the estimated preference parameters. I evaluate the policies based on household preferences from the 2006 survey to focus on the most recent year of data available. This allows me to interpret the simulation results as the effect of a policy change on welfare in a given year (as opposed to welfare changes in multiple years). As already noted, the three policies that I consider directly adjust prices faced by consumers. The price changes are fed directly into the logit probabilities computed based on the estimation results to obtain new demands for each vehicle.

[48] Anecdotal evidence suggests that vehicle manufacturers assume that consumers need a three year payback to be willing to buy a more fuel efficient vehicle. To the best of my knowledge there does not exist any evidence on how manufacturers perceive the distribution of consumer valuation of fuel costs.

I do not model the used vehicle market or scrappage market for two reasons. First, the policies that I consider only apply to new vehicles, implying that the largest welfare effects will be through the new vehicle market.[49] Second, my estimation model only applies to new vehicles.[50] And since there is no empirical basis for assuming that household preferences for used vehicles are identical to those for new vehicles, it seems most reasonable to avoid this assumption by leaving the used vehicle market out of the model.

To compute welfare effects of the policies, I broadly follow [17] and [3] by defining utility as the difference between two components: decision utility and internality utility. I define the internality utility as the difference between experienced utility and decision utility, which I assume is

$$V_{ijt} = \begin{cases} \eta(1 - WTP_i) fc_{ijt} & \text{if } WTP_i < 1 \\ 0 & \text{otherwise} \end{cases} \tag{2.12}$$

This equation defines internality utility as a fraction of the utility value of the present value of fuel costs for vehicle j (fc_{ijt}) for households that are inattentive to fuel costs, where η is the marginal utility of income. The fraction is equal to one minus household i's WTP for reducing fuel costs by one dollar. The smaller the household's WTP, the larger the internality utility for the household. Internality utility is positive for households that undervalue fuel costs. This expression is intuitive because households with WTP_i value $\eta WTP_i fc_{ijt}$ at the time of purchase

[49]In theory, the policies that I consider could be applied to the entire vehicle fleet. They have historically not applied to used vehicles, however, because doing so would likely involve a major administrative burden and would likely be politically infeasible.

[50]Extending the model to include used vehicles would make estimation computationally infeasible since doing so would increase the vehicle choice set to the thousands.

but experience ηfc_{ijt} while they own it.[51] This drives a wedge (equal to V_{ijt}) between their decision and experienced utility. To aggregate internality utility across consumers, I take the product of V_{ijt} with choice probabilities P_{ijt} and sum these products across households and markets. I then divide by the marginal utility of money to compute the dollar equivalent, which is

$$CS^n = \sum_i \sum_j \sum_t P_{ijt} \tilde{V}_{ijt}, \tag{2.13}$$

where

$$\tilde{V}_{ijt} = \begin{cases} (1 - WTP_i) fc_{ijt} & \text{if } WTP_i < 1 \\ 0 & \text{otherwise} \end{cases} \tag{2.14}$$

I compute the change in decision consumer surplus, $\Delta CS^d = CS^d_1 - CS^d_0$, with the formula derived in [110]. This form is a simple closed-form expression for consumer surplus when utility is linear in income. When utility is non-linear in income as it is in my model, it serves as an approximation to consumer surplus. McFadden [86] and Herriges and Kling [65] provide a simulation-based approach to compute consumer surplus for discrete choice models that have utility modeled as a non-linear function of income. I find that the simulation-based approach is computationally expensive to perform in my model and results in large margins of error.[52] Moreover, Herriges and Kling [65] find that the closed-form solution in Small and Rosen [110] serves as an accurate approximation of simulated

[51]This is true even if the household expects to sell the car before it reaches its lifetime since the re-sale value will include the existing present value of fuel costs.

[52]Herriges and Kling[65] claim that the computational burden of the simulation-based approach is the method's primary drawback. The computational burden in my model is especially pronounced because I model utility with random parameters. This requires an additional 200 iterations (equal to the number of Halton draws I use) of the simulation-based approach.

consumer surplus while involving little computational burden to compute. More importantly, the computed consumer surplus change that I find for the policies considered lie well within the range of recent estimates from the literature, suggesting that the approximation is sound.

Realized consumer surplus is total decision consumer surplus minus aggregate internality surplus:

$$CS^{*} = CS^{d} - CS^{n}. \tag{2.15}$$

The policies that I consider are not necessarily revenue neutral. I assume that any revenue raised by a policy, denoted by R, is returned lump-sum to consumers. Furthermore I assume that the revenue raised that is used as a subsidy, denoted by S, is raised with a non-distortionary head tax.[53] The cost of a policy is directly reduced by the amount of revenue generated by the policy, while the cost of a policy is directly raised by the amount of subsidy paid. The cost of a policy, denoted by C, is equal to the amount of net revenue raised negative of the change in decision consumer surplus minus the change in internality surplus plus the amount of revenue raised:

$$Cost = S - R - (CS_1^d - CS_0^d) - (CS_1^n - CS_0^n) = S - R - \Delta CS^d - \Delta CS^n. \tag{2.16}$$

Here the subscripts 0 and 1 denote the pre- and post-policy surpluses.

[53]The fundamental results of my analysis do not change when I assume that the subsidy payments are raised through a distortionary tax.

2.6.2 Evaluating Policies for Increasing Fleet Fuel Economy

I evaluate policies for increasing fuel efficiency relative to an "ideal" setting where a hypothetical policy can encourage all the households that have $WTP < 1$ to fully value fuel costs. I call this policy "Perfect Targeting" as it only influences the decisions of households that undervalue fuel costs. I simulate the internality benefits of this policy by taking the difference in internality consumer surplus between two settings: one where household preferences are modeled with the estimated preference parameters and one where all households have $WTP_i \geq 1$. To estimate fleet characteristics and internality consumer surplus for the latter setting, I assign preference parameters to households originally with $WTP_i < 1$ a value of β_i such that $WTP_i = 1$.[54] What we can expect from the Perfect Targeting Policy is an increase in fleet fuel economy as the households with an estimated $WTP_i < 1$ that would have bought low MPG cars instead by more fuel efficient vehicles when they have $WTP_i = 1$.

I evaluate the welfare effects of three policies: a gas guzzler tax, a feebate that is equivalent to a CAFE standard and a fuel efficient vehicle subsidy. A gas guzzler tax assigns a fixed tax rate on vehicles that have low fuel economy. The rate is usually applied to the manufacturer. There are two components of a gas guzzler tax: the rate and the threshold. The threshold determines which vehicles are affected by the tax. Vehicles with fuel economy below the threshold are taxed,

[54]This change intuitively represents a policy that provides households with information on fuel costs at zero cost. It also assumes that households optimally utilize this information without cost.

while those above are unaffected. The rate defines how much tax is paid per MPG below the threshold. Generally the tax is higher on vehicles well below the threshold. In the United States, the gas guzzler tax threshold is 22.5 MPG. The rate is an increasing function of the difference between the vehicle's fuel economy and the threshold.[55]

A fuel efficient vehicle subsidy is the mirror image of a gas guzzler tax: It assigns a subsidy rate on vehicles that have high fuel economy. A subtle difference that I do not analyze in my model is that the subsidy is usually available to the consumer and not the manufacturer.[56] Vehicles above a threshold level are subsidized. In the United States, most vehicle subsidies do not establish a threshold but instead are limited to vehicle classes.[57] For example, several state and federal initiatives have subsidized the purchase of hybrid vehicles while others currently subsidize electric vehicles [16].[58] To make the policies comparable, however, I model the subsidy as a rate-threshold policy.[59]

A feebate is essentially a gas guzzler tax alongside a fuel efficient vehicle

[55] A vehicle that has a fuel economy between 21.5 and 22.5 MPG is taxed at $ 1,000 while a vehicle that has a fuel economy less than 12.5 MPG is taxed at $ 1,000. See [40] for the complete gas guzzler tax schedule.

[56] In a model of perfect competition, the results of the model are invariant to where the tax or subsidy is applied. This is because the effect of each instrument is fully passed on to equilibrium vehicle prices.

[57] One exception is vehicle rebate programs which subsidize vehicles above a minimum fuel economy when the buyer of the new vehicle trades in an old, low MPG car to be scrapped. The largest such program in the United States was the 2009 Cash for Clunkers program, which had a MPG dependent subsidy rate and a class dependent threshold. See [82] for more details.

[58] These vehicle classes have average fuel economy well above the fleet-wide average.

[59] Modeling the subsidy as it is commonly seen in practice – that is, how subsidies apply to a small subset of fuel efficient vehicles like hybrids and electric cars – would artificially raise its efficiency costs since the scope of the policy would be sharply limited.

subsidy when the two policies share the same rate and threshold. A tax is levied on vehicles below the threshold and a rebate is assigned to vehicles that lie about the threshold. Like a gas guzzler tax, the taxes and rebates are usually assigned to manufacturers.[60] Several studies have documented that a feebate system can mimic any existing Corporate Average Fuel Economy (CAFE) Standard, which is the most comprehensive existing transportation policy for improving fleet fuel economy [98, 52].[61] Since 2007, CAFE Standards in the United States had been fixed at 27.5 MPG for passenger cars and 20.5 MPG for light trucks but are scheduled to dramatically increase over the next decade.[62] Therefore, in simulating the effects of a feebate I am also indirectly simulating the effects of an equivalent CAFE standard, so that my simulation results have a direct application to an existing U.S. policy.

To keep the policies comparable I assume that they each share the same threshold that I set equal to the fleet average fuel economy of 23.5 MPG. This threshold is represented in Figure 2.2 by the vertical red line. The density of fleet fuel economy is also plotted, showing that the distribution has a long right tail.[63]

[60]Several counterexamples exist in practice. For example, in 2008 California proposed a clean car discount program that would have made buyers of low MPG vehicles pay an additional fee of up to $ 2,500 [29]. The revenue generated from the program would then be rebated back to buyers of high MPG vehicles.

[61]A CAFE standard only requires setting a threshold at which a manufacturer's average fleet fuel economy must meet. The resulting shadow prices from a profit maximization problem of a manufacturer are analogous to the fees and rebates of a feebate program. See [98] for more details.

[62][85] provides an excellent summary and discussion of the new CAFE standards.

[63]This is primarily due to the presence of hybrid vehicles.

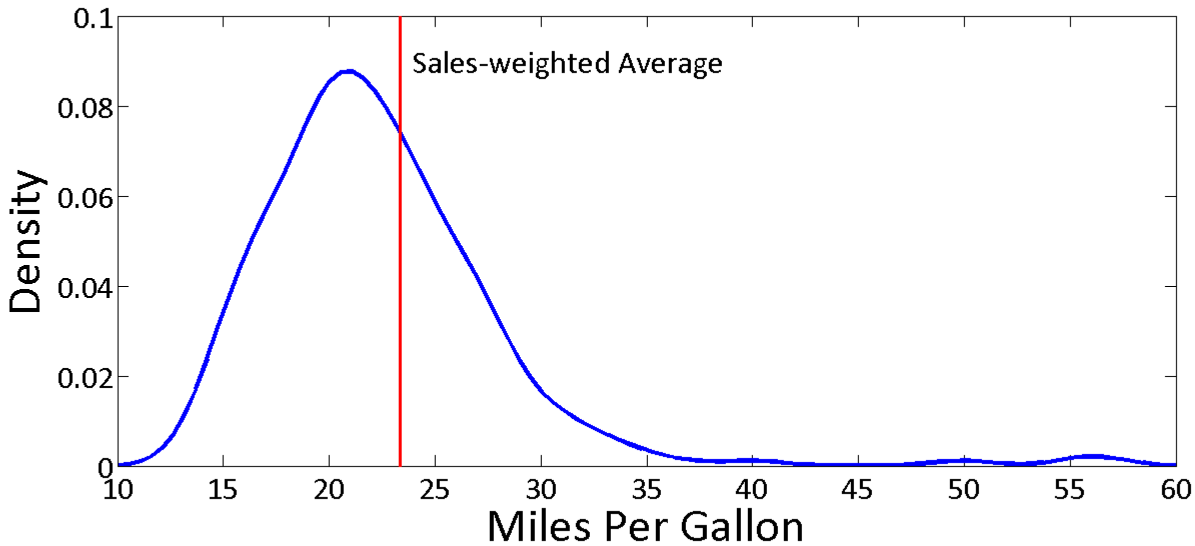


Figure 2.2: Distribution of Fuel Economy for the 2006 sample

Simulation results for the Perfect Targeting policy appears in the first column of Table 2.8. The first panel of the table reports changes to key fleet characteristics. Fleet fuel economy increases by 1.06 MPG and vehicle weight and horsepower fall. The change in internality consumer surplus is substantial. With perfect targeting, households can expect to benefit by about 125 dollars. To put this number in context, Jaconbsen (2013) finds that the welfare cost of increasing CAFE standards by one mile per gallon is at most 264 dollars.[64] Anderson and Sallee [7] find, however, that the welfare cost of increasing CAFE standards is substantially lower and lies between 8 dollars and 27 dollars per vehicle sold.[65] These estimates suggest, then, that perfect targeting can achieve private welfare benefits that can be as large as or even exceed the cost of existing fuel economy standards.[66]

I simulate the effect of one policy at a time relative to a setting where none of the policies are in place. I adjust the rate of each policy until the sales-weighted fleet fuel economy increases by the same MPG relative to the no policy baseline from the Perfect Targeting Policy. The simulation results for each policy appear in Table 2.8. The columns represent the simulation results for three policies relative to a benchmark that does not include any of the policies.

[64]This value includes the change in producer and consumer surplus and represents the welfare effects of a one-MPG increase 10 years after the change has been made. The change in producer surplus is equal to the change in manufacturer profits. The change in new car consumer surplus is 94 dollars after 10 years.

[65]Aggregating over the entire U.S. population yields a cost estimate of between 1 – 2 dollars per household.

[66]It is worth mentioning that these potential gains exist even when the average household fully values fuel cost savings.

Table 2.8: Simulation Results

Output	Perfect Targeting	Tax	Subsidy	Feebate
Fleet MPG Change	1.06	1.06	1.06	1.06
Hybrid Share Change	0.007	0.003	0.020	0.011
Fleet Horsepower Change	-8.302	-10.205	-4.758	-6.407
Fleet Footprint Change	-257.891	-310.008	-119.594	-176.357
Change in Internality Consumer Surplus	293.460	143.429	41.636	76.492
Change in Internality Consumer Surplus per household ($)	125	61	18	33
Change in Decision Consumer Surplus	–	-936.028	143.299	-71.848
Revenue[a]	–	662.720	0	209.066
Expenditure	–	0	406.883	324.079
Cost without internalities	–	273.308	263.584	186.861
Cost without internalities per household ($)	–	116	112	79
Cost with internalities	–	129.879	221.948	110.369
Cost with internalities per household ($)	–	55	94	46

[a] Revenue, expenditure and costs are reported in thousands of dollars.

Sales-weighted fuel economy increases by 1.06 miles per gallon in response to the three policies. The share of hybrids bought increases after each policy is put in place. This is because fuel efficient vehicles, including hybrids, become relatively cheaper than gas guzzlers. The hybrid share change is the most pronounced under the subsidy policy as hybrid buyers are offered very large price reductions.[67] Across all three policies, average horsepower and footprint falls. This is because fuel efficient vehicles are generally smaller and less powerful.[68] The inverse relationship between fuel economy, horsepower and size is strongest at the lower end of the fuel economy distribution. As a consequence, we see that the change in horsepower is about twice as large under the gas guzzler tax policy.

The second panel of Table 2.8 shows the change in internality consumer surplus.[69] The results reveal that internality consumer surplus is greatest under the tax policy and lowest under the subsidy policy. A gas guzzler tax achieves about one-half of internality consumer surplus increases relative to the Perfect Targeting policy, while the subsidy policy achieves only one-sixth. A feebate is substantially better at targeting than a subsidy but still falls far short of achieving

[67]This is because hybrids have a fuel economy rating well above the sales-weighted average of 23.5 MPG.

[68][73] estimates the trade-off between size, power and fuel efficiency in the United States and documents how it has evolved over time. He finds that increases in fuel economy standards will require significant reductions in vehicle size and power.

[69]Since my model does not condition household decisions on buying a new car, the change in internality consumer surplus can be decomposed into two components: substitution and purchase. The substitution component represents the welfare effect of household substitution away from low MPG vehicles to high MPG vehicles. The purchase component represents the welfare effect of households being encouraged to buy or discouraged from buying a new car. I find, however, that the purchase component is very small (less than five percent) relative to the substitution component. Therefore, I do not report the components separately.

the gains from perfect targeting. Two results can be summarized as the following. First, gas guzzler taxes are the most effective policy for targeting households that ignore fuel costs to buy more fuel efficient vehicles. Second, all of the policies are unlikely to achieve the potential internality consumer surplus gains since they influence the decisions of all households.

Decision consumer surplus change, revenue and expenditure are reported in the third panel of Table 2.8. The values are reported in thousands of dollars. Under the gas guzzler tax policy, the change in decision consumer surplus is negative because consumer surplus falls as households face higher prices for gas guzzlers. The tax, however, brings in over 680 thousand dollars. The cost of the tax policy, without considering welfare effects from internalities, is just over 250 thousand dollars. Moving to the subsidy policy, we see that consumer surplus increases by 143 thousand dollars as consumers face lower prices for fuel efficient vehicles. The subsidy costs the government over 406 thousand dollars, implying a net cost of the policy of 263 thousand dollars. The feebate policy on overall reduces consumer surplus by 71 thousand dollars as the consumer surplus lost from higher prices for gas guzzlers dominates the consumer surplus gained from lower prices for fuel efficient cars. Furthermore the policy requires a net expenditure of about 115 thousand dollars, bringing to the total cost of the feebate policy to 186 thousand dollars.

Are these values reasonable? To determine the plausibility of the cost estimates, I compute the cost of each policy per household. I find that the costs of raising fleet fuel economy by one mile per gallon with a feebate (or an equivalent CAFE standard) is 79 dollars per household. Jacobsen (2013) finds that the consumer surplus cost of a 1 MPG increase to the CAFE Standard is between 99 and 215 dollars per household.[70] Anderson and Sallee [7] use a loophole in the design of CAFE standards to provide empirical evidence suggesting that Jacobsen's estimates significantly overestimate the cost of CAFE standards. My estimate, while based on a highly stylized model, is located in the same ballpark as the estimates from these studies.

The cost of the feebate policy is significantly lower than the cost of the other two policies because it has broader coverage. It either taxes or subsidies every vehicle in the fleet, while the remaining policies only do one to a limited portion of the fleet. This suggests that a feebate (or an equivalent CAFE standard) is the most cost-effective instrument among the three policies.

There are two reasons why gas guzzler taxes are best at targeting. First, households that are inattentive to fuel costs will be more likely to buy fuel inefficient vehicles. An average household that is inattentive to fuel costs will tend to sort into vehicles with low MPG while a household that fully values fuel costs will tend to sort into vehicles with high MPG. I demonstrate this sorting by plotting the predicted choice probabilities of four different vehicles for a randomly selected household in my sample. I plot the predicted choice probabilities as a function of the household's WTP for reducing fuel costs by one dollar, which I

[70] These values represent the consumer surplus cost after one and 10 years of the program, respectively.

vary between zero and 1.50. Figure 2.3 shows the predicted choice probabilities for two gas guzzlers (Jeep Grand Cherokee, 19 MPG and Chevrolet Tahoe, 15 MPG) and two gas sippers (Nissan Altima, 25 MPG and Ford Focus, 28 MPG). Households that are inattentive to fuel costs are more likely to purchase one of the gas guzzlers as each of the low MPG vehicle choice probabilities exceeds the choice probabilities of the high MPG cars. On the other hand, households that fully value fuel cost savings are more likely to purchase one of the fuel efficient vehicles. In fact, the choice probability for the Ford Focus is almost three times as large as the choice probability for the Chevrolet Tahoe when the household is willing to pay one dollar.

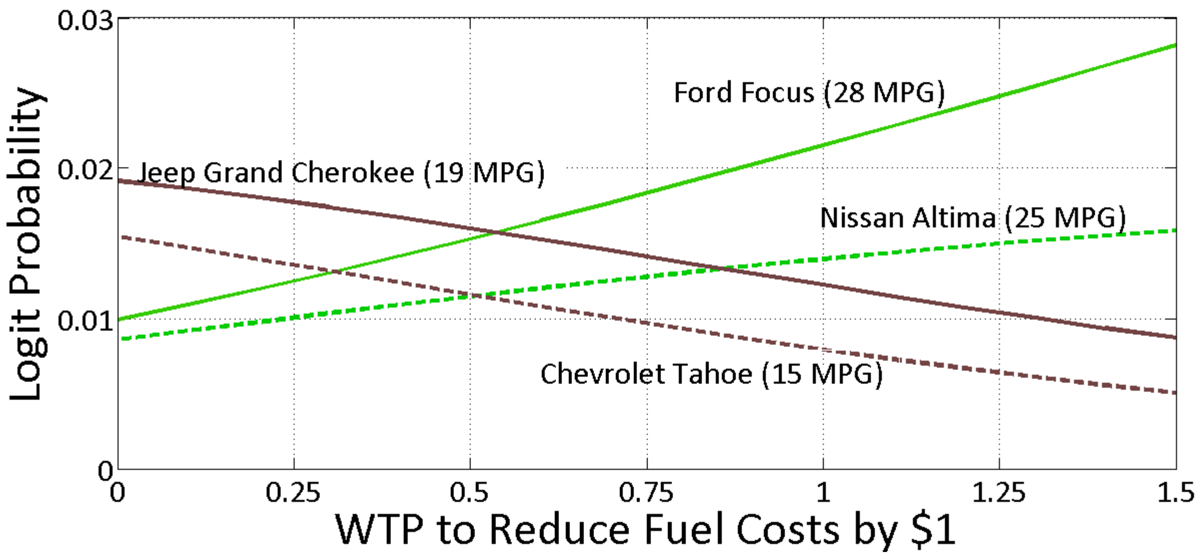
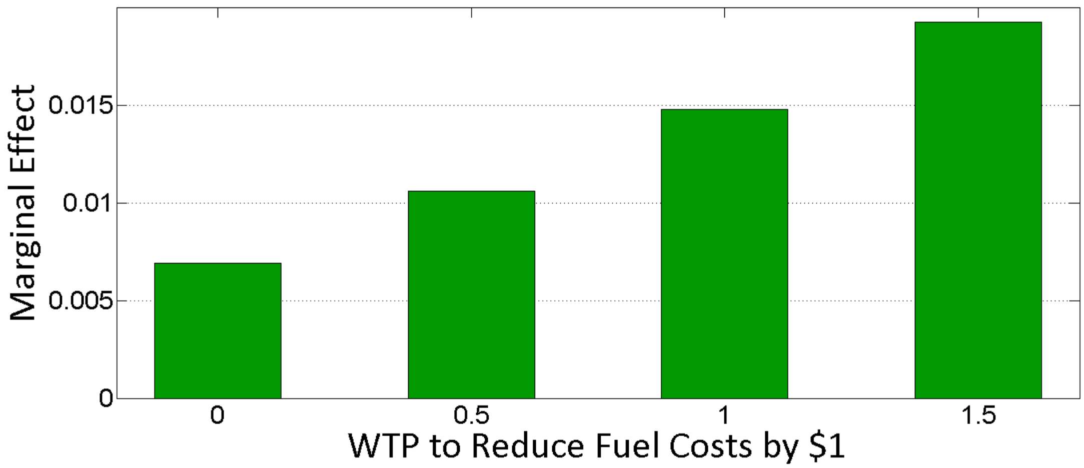
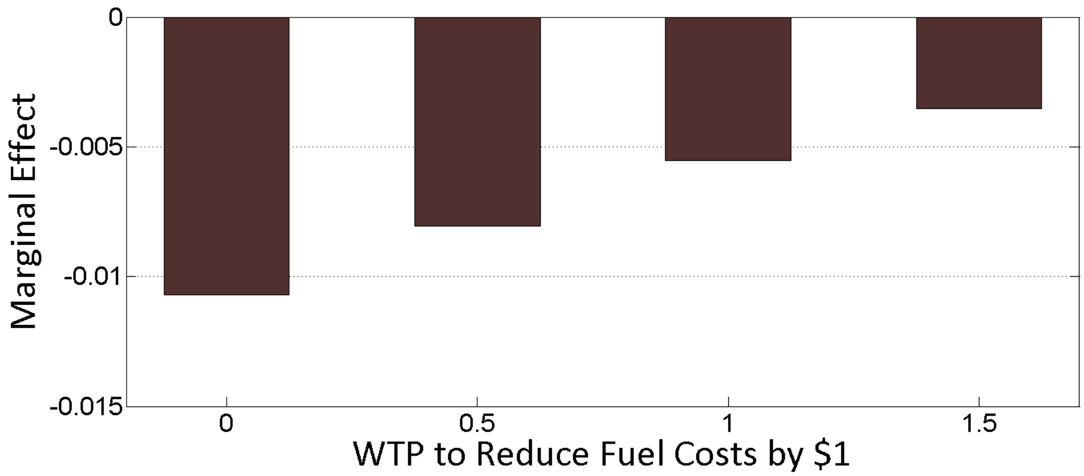


Figure 2.3: Sorting by Fuel Economy for Different Valuations of Fuel Costs

Second, the marginal effect of a price change of a household's probability to purchase a vehicle will be relatively large for either a household that is inattentive to fuel costs that is considering buying a gas guzzler or for a household that fully values fuel costs that is considering buying a fuel efficient car. Said differently, households that are inattentive to fuel costs will be most responsive to price changes to gas guzzlers, while households that fully value fuel costs will be most responsive to price changes to high MPG vehicles. This effect stems from the intuitive feature of logit probability models where the marginal effect of an attribute change is the largest for decision makers that have logit probabilities closer to 50 percent. This effect is illustrated in Figure 2.4 for two vehicles: a Ford Focus (high MPG) and a Chevrolet Tahoe (low MPG). Panel (a) shows the marginal effect of lowering the price of a high MPG vehicle on the choice probability for that vehicle of a randomly selected household. If the household has a low WTP for reducing fuel costs, they will be less responsive to the price change. A household that fully values fuel costs has a marginal effect that is more than twice as large as the marginal effect of the same household that ignores fuel costs. Panel (b) shows the marginal effect of raising the price of a low MPG vehicle on the choice probability for that vehicle of a randomly selected household. If the household has a low WTP for reducing fuel costs, they will be more responsive to the price change. A household that is inattentive to fuel costs has a marginal effect that is about twice as large as the marginal effect of the same household that fully values fuel costs.



(a) Logit Probability Marginal Effect of a $1 Subsidy to a High MPG Car (Ford Focus, 28 MPG)



(b) Logit Probability Marginal Effect of a $1 Tax on Low MPG Car (Chevrolet Tahoe, 16 MPG)

Figure 2.4: Logit Probability Marginal Effects of Price Changes to High and Low MPG Cars

Together, these effects explain why a gas guzzler tax achieves greater internality benefits than a fuel efficient car subsidy or a feebate. Households that are inattentive to fuel costs are most responsive to a gas guzzler tax and are least responsive to a subsidy or rebate to fuel efficient vehicles. On the other hand, households that fully value (or overvalue) fuel cost savings are most responsive to a subsidy and are least responsive to a gas guzzler tax. A gas guzzler tax effectively targets the households that bring about internality welfare benefits (e.g. those that are inattentive to fuel costs).

2.6.3 Additional Policy Implications

Four implications for evaluating other transportation policies emerge from my analysis. First, my analysis suggests that certain types of vehicle scrappage programs might be excellent at targeting households that undervalue fuel economy. The largest vehicle scrappage program, known as "Cash for Clunkers", paid households new vehicle subsidies for retiring low MPG vehicles.[71] The only households that were eligible for the program were those that owned fuel inefficient cars relative to the fuel economy of the new car purchased. As a consequence, the program likely screened out many households that fully value fuel economy, since these households are more likely to own high MPG

[71] Vehicles eligible for retired were required to be at least 4 MPG lower than the MPG of the new vehicle bought. The largest subsidy payment of $ was eligible only to households that scrapped a gas guzzler that had a fuel economy of 10 MPG lower than the new vehicle. See [82] for more details.

cars. Other retirement programs, including the Bay Area Air Quality District's (BAAQD) Vehicle Quality Program or the California Air Resources Board (CARB) Consumer Assistance Program, do not place requirements on the fuel efficiency of vehicles scrapped.[72] The efficiency of these programs may be improved if they add an upper limit to the fuel economy of eligible vehicles.

Second, my results have implications for overlapping policies in the transportation sector. In practice, more than one of the three policies that I consider are in effect at one time.[73] Recent literature on the economics of fuel economy standards identifies unintended consequences of overlapping or nested policy instruments [56, 98]. These studies find that adding policies on top of existing CAFE standards are ineffective at reducing gasoline consumption. The key mechanism at play here is that the new policies essentially relax the CAFE constraint faced by firms, which allow manufacturers to increase the sale of gas guzzlers. In the extreme case, the equilibrium effect of an additional policy in the presence of CAFE is that there is an increase in gasoline consumption.[74] From the results of my own work, we can be confident that this is indeed likely for fuel efficient vehicle subsidies. This is because these subsidies are relatively poor at targeting households that are inattentive to fuel costs. In contrast, adding a

[72]See [103] for an excellent summary of the BAAQD program. CARB's website `http://www.arb.ca.gov/msprog/avrp/avrp.htm` has detailed information on eligibility requirements for the Consumer Assistance Program.

[73]For example, in 2012, vehicle manufacturers were regulated by both and gas guzzler tax of 22.5 MPG and a CAFE standard of 32.8 MPG for passenger cars. In the same year, various state and federal incentives gave rebates to consumers who bought electric vehicles.

[74][98] finds that this is the case when a hybrid subsidy is put in place with an existing CAFE standard. The hybrid subsidy has no effect on the equilibrium fleet average fuel economy but increases vehicle ownership as the average vehicle price falls.

gas guzzler tax on top of a CAFE standard may be justified based on efficiency grounds. Adding a gas guzzler tax effectively increases the shadow cost on fuel efficient vehicles while keeping the shadow cost on fuel efficient vehicles constant.[75] As a consequence, the two policies together should be more effective at targeting inattentive consumers than a CAFE standard alone.

Third, Congress recently passed new CAFE standards that are planned to dramatically increase over the next decade. The 2013 standard for passenger cars is 34 MPG [95]. By 2025 the standard is scheduled to increase to 56 MPG [96].[76] As CAFE standards increase over time, they become more like a broad gas guzzler tax in the sense that a majority of vehicles will have a positive shadow cost. This feature will likely increase the efficiency of CAFE standards as they will make the most inefficient vehicles much more expensive in equilibrium.

Forth, in addition to becoming more stringent over time, CAFE standards have been reformed to depend on vehicle footprint. Each manufacturer is assigned a separate CAFE standard depending on the average footprint of the vehicles each manufacturer sells. Manufacturers that sell heavier cars are assigned a lower standard.[77] Footprint-based standards are likely to be worse at encouraging households that undervalue fuel economy to buy fuel efficient

[75]This result, of course, is incomplete without considering the general equilibrium effects of these policies. Although these effects can be large, it is difficult to deduce their size or direction without an analytical model that is not present in the current analysls. I therefore leave this exercise for future work.

[76]These values do not include the array of exclusions and bonuses written in the final ruling.

[77]The reported purpose for this reformulation is to avoid down weighting, which occurs when manufactures reduce vehicle weight to improve fuel economy. Prior to this reformulation each manufacturer was assigned the same standard.

vehicles. Households that undervalue base their purchase decisions on other vehicle attributes, such as vehicle weight and safety. Since vehicle footprint is highly and positively correlated with weight, households ignoring fuel costs will sort into heavier vehicles with larger footprints and lower fuel economy.[78] Under the original standard, these vehicles would become more expensive as CAFE standards are tightened, which would encourage households to buy other, more fuel efficient cars. Under the modified standards, however, these vehicles have a smaller shadow cost of CAFE and therefore become less expensive (holding the overall stringency of CAFE constant). As a result, the footprint-based standards actually encourage households that are inattentive to fuel costs to buy heavier, less fuel efficient cars. Even as the overall level of strigency of CAFE standards increase over time, the footprint-based reformulation may eliminate the incentive for households that undervalue fuel economy to buy high MPG vehicles.

2.7 Conclusion

The caveats mentioned above may have significant welfare effects that should be included in future analysis of policies with the goal of reducing gasoline consumption and its associated externalities. I abstain from exploring these effects because my estimation and simulation frameworks do not include necessary modeling details to carry out a careful analysis. To better understand

[78] Among new 2006 vehicles, the correlation coefficient between vehicle footprint and weight is 0.80. The correlation coefficient between vehicle footprint and fuel economy is −0.59.

how consumer heterogeneity influences the welfare effects of footprint-based CAFE standards, I require a model of imperfect competition among vehicle manufacturers. This competition is likely to lead to large welfare effects on the producer side as well as the consumer side. It would also be a fruitful pursuit to consider how car manufacturers respond to footprint-based standards with different levels of knowledge about the distribution of consumer preferences for fuel economy.[79]

Another limitation of my work is that my model is static. Dynamic effects, such as how different types of consumers make vehicle purchase decisions as CAFE standards become more stringent, are likely to be extremely important for evaluating CAFE standards over the next decade.

Even without these additional modeling details, however, my estimation and analysis reveals four key findings. First, I find that there is substantial heterogeneity in how households value fuel economy. By estimating a mixed logit discrete choice model of new vehicle demand, I find that households on average fully value the gasoline cost savings from better fuel economy. Furthermore the estimation results suggest that about 31 percent of households appear to be inattentive to vehicle fuel costs, leaving room for some types of fuel efficiency policies to increase private welfare. These estimates suggest that there is potential for substantial welfare gains from encouraging households that undervalue fuel

[79] [67] finds that in the context of the Energy Star Program, firms can price discriminate to exploit the heterogeneity in energy cost valuation, which reduces consumer surplus and increases producer surplus.

costs to buy more fuel efficient vehicles.

Second, I show that the estimated distribution for fuel economy valuation has key policy implications that I explore with a simple simulation model of the new vehicle market. With the simulation I find that a gas guzzler tax is relatively good at encouraging households that are inattentive to fuel costs to purchase more fuel efficient vehicles. I also find, however, that a feebate (or an equivalent CAFE standard) is more cost-effective at increasing fleet fuel economy because it has a much more broad coverage.

Third, I show that subsidies or rebates to fuel efficient vehicles, like hybrid car rebates or more recently electric vehicle subsidies, are poor at targeting. These policies have the largest influence on households that already fully value fuel economy to buy high MPG cars. As a result, for a given increase in fleet fuel economy, relatively few households that are inattentive to fuel costs are encouraged to buy a fuel efficient vehicle when offered a subsidy.

Fourth, these policies do not come close to achieving the potential welfare gains from a policy that only influences the decisions of households that undervalue fuel economy. This seems reasonable since none of the policies are designed to only influence the decisions of this subset of the population. One potential avenue for future work in this area may be to identify household demographics characteristics that are correlated with WTP for fuel cost savings so that future policies can be engineered to provide incentives to households with $WTP_i < 1$.

Together, these results suggest that heterogeneity in consumer valuation of fuel costs has critical implications for designing energy policy in the transportation sector. Moreover, the results have policy implications for policies in other sectors as well. [67] finds that there is substantial heterogeneity in consumer valuation of energy costs of durable household goods, including refrigerators. He finds that there is a substantial fraction of households that do not value energy cost savings when making a durable goods purchase. As a result, minimum standards, such as those for light bulbs and household appliances, should be efficient policies for targeting households that undervalue or ignore fuel costs. This is because a minimum standard shares a similar property to a gas guzzler tax in that it only directly influences equilibrium prices of products that are the least energy efficient. The efficient design of other subsidy policies, including carbon offset mechanisms that are linked with cap-and-trade programs for reducing greenhouse gases, depends on the heterogeneity of business-as-usual emissions among offset projects [14]. Obtaining estimates of this heterogeneity and evaluating how different instruments encourage desirable projects to opt in are necessary for designing cost-effective policies for limiting global warming.

CHAPTER 3

DESIGNING EFFICIENT MARKETS FOR CARBON OFFSETS WITH DISTRIBUTIONAL CONSTRAINTS

3.1 Introduction

The design of markets for carbon offsets from unregulated sectors, to complement cap-and-trade programs in regulated sectors, is a central issue in environmental and climate policy. Such markets could, if designed appropriately, reduce the overall economic costs of climate change mitigation programs [42, 74]. Allowing capped sectors to use offsets essentially broadens the affected sources that are able to reduce emissions. When capped and uncapped sources of emissions are open to trade emissions credits in the form of carbon offsets, a reduction target can be achieved at a lower cost relative to a program that does not let the uncapped sector opt in [94, 27].

This form of cost containment, however, may break the cap established for regulated sources if the mitigation from uncapped sources would have happened in the absence of the program. The problem of non-additionality, or the awarding of carbon offsets to uncapped sources that do not perform mitigation, is a central source of criticism because of its adverse emissions consequences [94, 27]. The problem stems from the fact that programs cannot fully observe business-as-usual (BAU) emissions from uncapped sources, since these emissions are a hypothetical what if that never takes place if the source opts in. If the source would have reduced emissions anyway, then it is awarded non-additional offsets that are then sold to capped sources. The non-additional offsets contribute toward an increase in overall emissions, even if economic efficiency improves because of the additional offsets. This non-additionality, often discussed in terms of the integrity of the cap, is a major worry for key stakeholders, and thus for policy makers.

There is a well-known solution to this problem of cap integrity. Programs can deal with non-additionality by tightening the cap on the regulated sector sufficiently that total emissions remain unchanged [91]. However, this policy involves a transfer of rents from the capped sector (if permits are grandfathered) to the uncapped sector. As we will see later on in this paper, this transfer can be very large for the proposed federal cap-and-trade program in the United States. Our numerical calibrations suggest a transfer of the order of 30 percent of the pre-offsets market rent in the capped sector. Not surprisingly, these transfers will be resisted strongly by firms in the regulated sector.

There are three key alternative methods being discussed in the offsets policy area for handling the problem of additionality, including (i) more stringent emissions baselines for sources in the uncapped sector; (ii) trade ratios for offsets relative to allowances, where a unit of offset supplied from the uncapped sector translates into less than one unit of emissions permitted in the capped sector; and (iii) a limit on the use of offsets for compliance in the capped sector [27, 74]. It should be obvious that each of these three instruments reduces the total supply of offsets, and hence the rent transfer from the capped sector. But the impact of each of these on the additional versus non-additional composition of offsets is not at all clear and requires careful analysis. Further, the compositional effect relative to the distributional effect for each of these instruments needs to be quantified. This leads then to the question addressed in this paper – which instrument is best, for which objective?

Recent studies have taken some first steps in analyzing the welfare and distributional implications of opt in programs. [91] studies this problem in the context of the SO_2 opt-in provision where uncapped units were allowed to opt in and receive a quantity of allowances based on historical emissions. In a setting where units have private information on business-as-usual (BAU) emissions, the first best can be achieved by raising the allocation to uncapped units so that all of them opt in and lowering the permit allocation to capped units. Van Benthem and Kerr [116] compare the efficacy of alternative methods for alleviating adverse selection in avoided deforestation programs. They find that increasing the scale of opt in projects alleviates (and, in the limit, can eliminate) the problem of adverse selection. They also compare the efficacy of imposing trade ratios and adjusting offset project baselines. They find that an optimal policy includes a combination of a trade ratio and stringent baselines, a result that is consistent with our own findings. This study, however, does not evaluate the welfare implications of limiting the use of offsets and focuses its simulations on an international offsets scheme. Our study compliments Von Benthem and Kerr by focusing on the efficiency and distributional implications of a domestic offset program.[1]. Like Van Benthem and Kerr, we document an important trade-off between efficiency gain and rent transfer. We evaluate this trade-off, however, for distinct domestic sectors (e.g. capped sectors like electricity generation, petroleum refining and cement manufacturing and uncapped sectors like agriculture and forestry). We find that different offsets policies lead to substantially different rent transfers between these sectors, making some offsets policies more politically feasible than others.

[89] evaluates the effectiveness of sectoral crediting mechanisms using a similar model of adverse selection. He shows that there exists a significant trade-off between efficiency and rent transfers, and that uncertainty in BAU emissions makes these mechanisms very poor methods for reducing emissions. This study, however, focuses on national transportation sectors and does not consider the relative efficiency of alternative instruments for dealing with additionality among individual offsets projects.

Our paper extends the literature in several ways. First, we extend prior analyses of adverse selection in opt-in emissions trading programs by deriving analytical welfare formulas for instruments currently being adopted in cap-and-trade programs. Our formulas allow us to make general statements about the differences between the instruments and to provide clear policy recommendations based on these differences.

[1]While there exist cap-and-trade programs that allow international offsets, there are several examples that only allow domestic sources to opt in, including the Regional Greenhouse Gas Initiative and the program under the California AB 32 Global Warming Solutions Act.

Second, we provide an assessment of three instruments for the level and composition of offsets, holding constant the cap on the regulated sector. We then use this to conduct an analysis of the efficiency and distributional implications of each instrument. Furthermore, we compare policies based on efficiency and on rent transfers, which lead to critical trade-offs that we explore analytically and numerically. This exercise contrasts with existing literature that focuses solely on the efficiency aspect of different offset policies.[2]

Third, we numerically calibrate the analytical model to analyze federal U.S. greenhouse gas (GHG) cap-and-trade legislation as described in the 2009 Waxman-Markey bill. With our numerical model we are able to compute the welfare and emissions impacts of alternative second-best policies. We are also able to compute the welfare cost associated with avoiding rents from being transferred across sectors to implement the first-best solution.

Our major findings are fourfold. Our first result suggests that coupling the instruments can achieve greater efficiency than using them individually. We find that the second-best policy couples a trade ratio less than one with a very stringent baseline. While a very stringent baseline eliminates most of the supply of non-additional offsets, it crowds out the supply of additional offsets. The trade ratio is set below one to increase the price of offsets and boost up the supply of

[2]Comparing the efficiency gains to the distributional implications is especially important for designing markets for carbon offsets. In particular, the key concern with the first-best mechanism presented in [91] is that there may be a significant transfer of rents across sectors of the economy. If this rent transfer turns out to be small, then it may be feasible to implement in practice, which would make the discussion of second-best policies irrelevant.

additional offsets.

This mechanism may not be politically feasible as trade ratios less than one appear, independent of the other instrument choices, to increase aggregate emissions, as capped firms need less than one offset to account for one of its own emissions. Our second result addresses the question of how the policy maker should set the three instruments when it cannot select a ratio less than one. In this setting, the baseline is the best instrument for maximizing welfare. When the baseline is set at its optimum level, the trade ratio should be set at one and the offsets limit should be non-binding. The reason for this is that adjusting the baseline attacks the problem of non-additionality directly, while the other two instruments can only approach the issue indirectly.

Third, comparing the three instruments, our numerical calculations show that the welfare cost per unit of avoided redistribution from the capped sector is the lowest for the baseline. However, the numerical value of this ratio is below standard estimates for the marginal excess burden of public funds. This result suggests that if the policy maker chooses among the policy options of sacrificing welfare to avoid one dollar of transfers or allowing the rent transfer to take place but compensate capped firms through revenues generated from a labor tax, they should choose the former as it is less costly per dollar of transfers.

Fourth, when the baseline instrument is not fully reliable, as in the case of international offsets, then the other two instruments come into their own. In this case we show that the trade ratio instrument is superior to the limits instrument and that the efficient trade ratio is above one.

The plan of the paper is as follows. Section 2 sets out the basic analytical model and derives analytical results as the basis for the numerical model. Section 3 develops the calibration of the numerical model for the US and presents the main results. Section 4 provides further analysis and Section 5 concludes.

3.2 The Analytical Model

In this section we develop an analytical model to isolate the channels exploited by various instruments that regulate carbon offsets markets.

3.2.1 Model Assumptions

The model has two sectors: A *capped* or *unregulated sector* and an *uncapped* or *unregulated sector*. Each sector includes a unit mass of firms that are capable of reducing emissions.[3] A regulator controls emissions by establishing a cap-and-trade program requiring firms in the *capped sector* to hold a permit or an equivalent quantity of offsets for every unit of pollution they emit. The regulator encourages uncapped firms to opt into the program by allowing them to sell offsets to capped firms.[4]

[3]Emissions reductions either occur through abatement or sequestration. Reductions from abatement result from actions that lower the release of emissions into the atmosphere. Carbon sequestration is the process of capturing and storing emissions.

[4]There are several reasons why some sources are capped while others are not. The most prominent reason is because monitoring and verification costs for some sectors are substantially

In our notation, the subscript $j = \{r, u\}$ denotes the regulated and unregulated sector, respectively, while the superscript i denotes firm i. Pre-intervention levels of variables are further subscripted by 0. Emissions are denoted by the variable e. Thus e^i_{j0} is the emission level of firm i in sector j in the pre-intervention scenario. This is also the business-as-usual (BAU) level of emissions. Firm i in sector j has a marginal cost of emission reduction c^i_j. This is assumed to be the same pre and post intervention. Thus the subscript 0 is suppressed. The values of e^i_{j0} and c^i_j are firm $i's$ private information. The regulator does not observe e^i_{j0} or c^i_j but observes density functions for each variable.

The policy intervention has two components. The the regulator establishes a cap-and-trade program by grandfathering A tradable permits to capped firms.[5] At the same time, the regulator sets emissions baselines for uncapped firms, b^i. Baselines attempt to measure BAU emissions of uncapped firms and are used to reward these firms for sequestration or emissions reductions.[6] Capped firms observe their permit allocation and make abatement decisions and uncapped firms observe their emissions baseline and make offset supply decisions. Firms

higher than they are in other sectors [108]. Other reasons include legal and political constraints and property rights issues [62]. Governing bodies generally have power to prevent harms (by preventing carbon emissions through abatement) but they cannot force the private production of benefits (by forcing emissions sequestration). The property rights issue involves international participation. While the United States, Europe and other developed countries may be willing to develop an emissions target, other countries may not. The US cannot force the participation of other countries, but it can encourage them to participate through an offsets program.

[5]We do not consider the possibility that permits are auctioned. In the most recent U.S. climate bill and in many existing cap-and-trade programs including Caifornia's program within the Global Warming Solutions Act, a large fraction of permits are freely allocated at the beginning of the programs.

[6]Setting a baseline is required for any opt-in policy. The credited reductions are determined by the agent's behavior in relation to the baseline. See [11] for a formal theoretical treatment.

make decisions based one their own BAU emissions, marginal costs of emission reductions and market prices for permits and offsets.[7]

We assume that BAU emissions are drawn from a sector-specific probability density function with support $e^i_{j0} \in [\underline{e}_{j0}, \overline{e}_{j0}]$ where each e^i_{j0} is independently and identically distributed according to the cumulative distribution function $Y_j(e_{j0})$ with mean $\mathbb{E}(e_{j0})$. Marginal costs are constant and satisfy $c^i_j \in [\underline{c}_j, \overline{c}_j]$ and are independently and identically distributed according to the cumulative distribution function $Z_j(c_j)$.[8] To keep the model analytically tractable, we assume that the distributions are independent.[9] In addition to lowering emissions, uncapped firms can sequester emissions. We assume that each uncapped firm has the same sequestration potential of $\alpha \leq 0$.[10]

Capped Firm Problem

[7]These assumptions are consistent with [91]. An alternative assumption would be that firms form expectations of market prices which would likely change capped and uncapped firm decisions depending on how the expectations are formed. To the best of our knowledge there does not exist evidence on how offset suppliers form price expectations. We adopt the simplest approach by assuming all firms observe all relevant market variables.

[8]Although individual firms have constant marginal costs, because marginal costs vary across firms, the aggregate marginal cost curves for each sector are not constant. Furthermore, in the analytical model and welfare formulas that we present below, we do not assume a specific distribution for marginal abatement costs. In our simulation we assume that the distribution for marginal costs of uncapped firms is uniform. This implies that the marginal cost curve for the uncapped sector is linear.

[9][42] demonstrate that correlations between marginal abatement costs between capped and uncapped sectors lead to small increase in compliance costs. Under the most extreme correlation considered, [42] find that compliance costs are about nine percent higher than the case without correlation.

[10]We represent sequestration of emissions as a negative quantity so that net emissions equals the sum of emissions and sequestration.

We assume that capped firm i is grandfathered permits a_0^i.[11] We define the rent generated by the establishment of the cap-and-trade program as the equilibrium value of all of the permits allocated to capped firms. The rent generated from the grandfathering equals $p_e a_0^i$, where p_e is the equilibrium permit price.[12] Firm i uses permits to comply with the cap-and-trade program or the firm sells them to other firms.[13] In addition, the firm can buy offsets, f, or abate its emissions. Firm i minimizes compliance costs by choosing emission level e_r^i, permit sales a^i and offset purchases f^i to solve for

$$\max_{\substack{0 \leq e_r^i \leq e_{r0}^i \\ a^i \geq -a_0^i \\ f^i \geq 0}} \left\{ p_a a^i + p_f f^i + c_r^i (e_{r0}^i - e_r^i) \right\} \text{ subject to} \tag{3.1}$$

$$a^i + a_0^i + f^i \geq e_r^i. \tag{3.2}$$

If $a^i < 0$, the firm is a net seller of permits, and if $a > 0$, it is a net buyer.[14] Permits are bought and sold at the equilibrium permit price, p_a, while offsets are bought

[11] The integral summation of individual firm permit allocations equals the aggregate permit allocation, $\int a_0^i di = A$.

[12] If all of the permits were to be auctioned, then capped sector rents would simply become government revenue. In this setting, government revenue adjusts under a policy prescription by the same amount that capped sector rents adjusts in the case that all permits are grandfathered.

[13] We abstract from dynamic aspects of cap-and-trade programs by considering a single compliance period. These aspects include permit banking and borrowing across compliance periods. Allowance banking and borrowing allow capped firms to smooth abatement costs over time by shifting emissions reduction responsibilities from one year to another. This mechanism has the effect of flattening the time path of emissions reductions and permit prices. See [99] for a theoretical treatment of banking and borrowing. [43] estimate the cost-savings from allowing firms to bank and borrow permits.

[14] Firm i's solution is to abate its emissions if it has a marginal cost of abatement that is less than the equilibrium permit price. In the absence of market power and transaction costs, the program will minimize compliance costs among capped firms [92]. Furthermore, the initial allocation of permits, a_0^i, will not influence the equilibrium, a manifestation of Coase's theorem [31]. For studies that consider market power and transaction costs, see [61] and [112].

at the equilibrium price p_f. The first-order conditions imply that the prices are equal in equilibrium:[15]

$$p_a = p_f. \tag{3.3}$$

Only firms with marginal cost of abatement less than c^i will reduce emissions below their BAU emission levels. These firms will reduce their emissions down to zero. Total abatement by the capped sector, denoted by q_r, is given by

$$q_r = \int_{\underline{c}_r}^{p_a} \int_{\underline{e}_{r0}}^{\overline{e}_{r0}} e_{r0} dY_r dZ_r. \tag{3.4}$$

Total abatement costs of the capped sector, denoted by C_r, are

$$C_r = \int_{\underline{c}_r}^{p_a} \int_{\underline{e}_{r0}}^{\overline{e}_{r0}} c_r e_{r0} dY_r dZ_r, \tag{3.5}$$

Note from these expressions that C_r can be written as a function of q_r, $C_r(q_r)$, by substituting out p_a.

Uncapped Firm Problem

Uncapped firms can opt into the cap-and-trade program by voluntarily selling offsets to capped firms.[16] For an uncapped firm to generate an offset, the regulator sets an emissions baseline for the firm. As the regulator cannot observe

[15]In Section 3.2, we will show that this equilibrium condition is distorted when the regulator introduces alternative instruments to regulate the supply of offsets.

[16]We do not distinguish between domestic and international offsets in our analytical model. We consider the case of international offsets in our sensitivity analysis when we expand the supply of offsets by adjusting down the upper bound of the uncapped sector marginal abatement cost distribution. We leave for a future exercise the joint determination of separate instruments for domestic and international offsets.

firm-specific BAU emissions, assigning baselines collapses to the decision of setting a common baseline for all uncapped firms.[17] We denote the common baseline by b.[18]

Uncapped firm i makes two decisions. First, the firm decides whether to opt in to the program. Second, it makes an emissions choice. If firm i opts in, it solves the following problem:

$$\pi^i = \max_{\alpha \leq e_u^i \leq e_{u0}^i} \left\{ p_f(b - e_u^i) - c^i(e_{u0}^i - e_u^i) \right\}. \tag{3.6}$$

Firm i opts in if $\pi^i \geq 0$. If $\pi^i < 0$, then firm i does not opt in and chooses $e_u^i = e_{u0}^i$.

The general behavior of uncapped firms is illustrated in Figure 3.1.[19]

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[17] We adopt this assumption for simplicity. Our results are insensitive to this assumption since the regulator only observes the aggregate distribution of BAU emissions. In practice the regulator can assign baselines at various scales, including assigning a baseline for an entire sector. See [74] for more details.

[18] In practice, baselines are assigned on a project-by-project basis and usually follow project-type protocols. (In the California AB 32 cap-and-trade program, there is a different protocol for the four project types that are currently allowed, including separate protocols for non-urban afforestation, urban afforestation, livestock and ozone depleting substances.) Our assumption of a common baseline is equivalent to a model where project-specific baselines are assigned as in [116], [89] and [14]. In each of these models, the policy maker observes a noisy measurement of BAU emissions for each project and assigns a baseline as a function of this measurement. As a consequence, projects with a measurement that is higher than their BAU emissions may be assigned a baseline that lies above its BAU emissions, as is the case for firms in areas A_4 and A_5 in our model. Projects with a measurement that is lower than their BAU emissions may be assigned a baseline that lies below its BAU emissions, represented by firms in areas A_1, A_2 and A_3 in our model. We represent the magnitude of the measurement noise in the models of [116], [89] and [14] by the heterogeneity in uncapped firm BAU emissions. In both model types, the greater the measurement noise or heterogeneity in uncapped firm BAU emissions, the greater the supply of non-additional offsets, the lower the quantity of under-credited emissions reductions and the lower the supply of additional offsets.

[19] Uncapped firms have three possible actions: do not opt in, opt in and reduce their emissions, or opt in and do not reduce their emissions. Firms located in areas A_1 and A_2 do not opt in and perform no abatement; firms located in areas A_3 and A_4 decide to opt in and abate the maximum amount $e_{u0}^i - \alpha$; Firms located in A_5 opt in and perform no abatement.

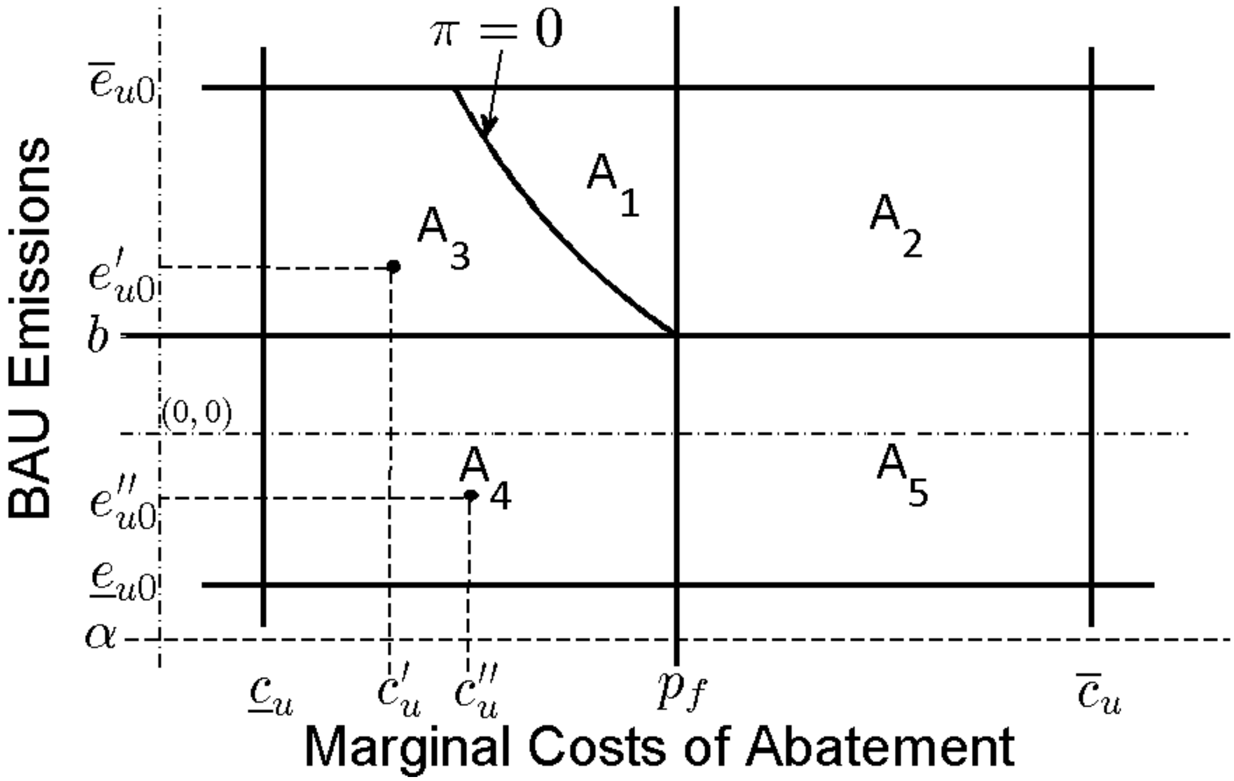

Figure 3.1: Decisions of Uncapped Firms

The horizontal axis measures marginal abatement costs of uncapped firms. The vertical axis measures BAU emissions of uncapped firms. The horizontal dashed line where BAU emissions equal α represents sequestration potential for all uncapped firms. Firms in area A_2 do not supply offsets because they have marginal costs of abatement that exceed the marginal return from supplying an offset, p_f. For firms with abatement cost less than p_f, the decision to supply offsets or not depends on how much larger than the baseline b are the BAU emissions e^i_{u0}, since this gap will have to be bridged and those abatement costs paid before offsets can be claimed when emissions go below b. The curve separating areas A_1 and A_3, denoted by $\pi = 0$, represents firms that are just indifferent to supplying offsets. The curve is obtained by substituting $e^i_u = \alpha$, setting the objective function in (3.6) equal to zero and isolating e^i_{u0}:

$$e^i_{u0} = \frac{p_f(b-\alpha) + c^i_u \alpha}{c^i_u}. \tag{3.7}$$

Note that this curve cuts the vertical axis at $\tilde{e}_{u0} = \min\left\{\overline{e}_{u0}, \frac{p_f b}{c_u}\right\}$. Firms in areas A_1 and A_2 do not supply offsets. Firms in areas A_3, A_4 and A_5 do supply offsets, but these have different implications for emissions reductions. An offset is *additional* if it corresponds to actual reductions in emissions. Additional offsets are sold by firms in regions A_3 and A_4, as the firms in these regions sell offsets that are created by reducing emissions. We denote the total amount of these as q_u. An offset is *non-additional* if it does not correspond to emissions reductions. These types of offsets are sold by suppliers with BAU emissions below the baseline that are able to claim offsets up to the baseline without actually reducing emissions. We denote the total amount of non-additional offsets by E_{NA}. Non-additional offsets are sold by firms in regions A_4 and A_5.[20] A firm that is characterized by the point (c''_u, e''_{u0}) opts in and earns additional and non-additional offsets since its BAU emissions fall below b and because it chooses to reduce its emissions further to $e''_u = \alpha$. But there also exists a quantity of emissions reductions that does not create offsets. Firms in area A_3 contribute to this type of reduction, which we call *under-credited emissions reductions* and denote by E_{UC}.[21] The quantity of under-credited emissions reductions by a firm in region A_3 is given by the difference between the firm's BAU emissions and its baseline, $e^i_{u0} - b > 0$.[22] A firm that is characterized by the point (c'_u, e'_{u0}) opts in, is under-credited and earns additional offsets since its BAU emissions lie above b and because it chooses to reduce its emissions to $e'_u = \alpha$. The quantities of q_u, E_{NA} and E_{UC} are given by

$$q_u = \int_{\underline{c}_u}^{p_f} \int_{\underline{e}_{u0}}^{\tilde{e}_{u0}} (e_{u0} - \alpha) dY_u dZ_u, \tag{3.8}$$

$$E_{NA} = \int_{\underline{c}_u}^{\bar{c}_u} \int_{\underline{e}_{u0}}^{b} (b - e_{u0}) dY_u dZ_u, \tag{3.9}$$

$$E_{UC} = \int_{\underline{c}_u}^{p_f} \int_{b}^{\tilde{e}_{u0}} (e_{u0} - b) dY_u dZ_u. \tag{3.10}$$

[20]Firms in area A_4 sell both additional and non-additional offsets. These are firms that are over-credited with non-additional offsets as the baseline is above their BAU emissions. These firms, however, also mitigate emissions because their marginal cost of mitigation is less than the equilibrium offsets price. The firms earn additional offsets from these mitigated emissions.

[21]The existence of these reductions has the effect of lowering aggregate emissions. In a companion paper, [14] use a simulation analysis to investigate the relative magnitude of under-credited emissions reductions to non-additional offsets for different levels of offset prices and baseline stringencies.

[22][107] discusses how various policy instruments, including adjusting baselines below BAU, can be used to achieve emissions reductions beyond those credited as offsets.

The costs of emission reductions in the uncapped sector, C_u, are given by

$$C_u = \int_{\underline{c}_u}^{p_f} \int_{\underline{e}_{u0}}^{\tilde{e}_{u0}} c_u(e_{u0} - \alpha) dY_u dZ_u. \tag{3.11}$$

3.2.2 Welfare

We define welfare as the difference between the benefits and costs of emissions reductions. Benefits of emissions reductions are defined by the function $B(\cdot)$ and satisfy $B'(\cdot) > 0$. Let e_{r0} be the pre-intervention level of emissions in the capped sector and A be the grandfathered permits. Then $\overline{q} = e_{r0} - A$ is the reduction target for the regulated sector. To calculate total emissions reductions, we need to subtract non-additional offsets, E_{NA}, and add under-credited emissions reductions, E_{UC}. To get the total abatement in the capped sector, q_r, we further subtract additional offset supply from the uncapped sector, q_u. With these specifications, we write welfare W as

$$W = B(\overline{q} - E_{NA} + E_{UC}) - C_r(\overline{q} - E_{NA} + E_{UC} - q_u) - C_u. \tag{3.12}$$

The first-best solution equalizes marginal benefits and marginal costs of emissions reductions across sectors. [91] studies a similar problem in the context of phase in emissions trading programs such as Phase 1 of the Acid Rain Program where some sources of emissions can opt in and become regulated.[23] He demonstrates that the first-best solution can be achieved by adjusting the opt-in allocation to the

[23]In a related paper Montero estimates the welfare effects of the opt in provision of the Acid Rain Program. He finds that a majority of opt in units were over-allocated permits, leading to a small increase in the aggregate emissions cap [90].

point where all unregulated units opt in and by adjusting the capped unit permit allocation to account for the supply of over-allocated permits. In our model, the first best can be achieved with a similar strategy, where the baseline is set to the point where all uncapped firms opt in and where the permit allocation is adjusted to account for the supply of non-additional offsets. The baseline is set at the upper bound of the uncapped sector BAU emissions distribution ($b = \overline{e}_{u0}$) so that every uncapped firm opts in. The high baseline generates a supply of non-additional offsets, E_{NA}, that reduces aggregate emissions reductions from the program.[24] To account for this quantity, the regulator increases the reduction target $\overline{q}$ from $\overline{q} = q^*$ to $\overline{q} = q^* + E_{NA}$,where q^* would have been the reduction target had all offsets been additional.[25]

Distributional Consequences of the First-Best Solution

The mechanism for achieving the first-best solution outlined above leads to a significant transfer of rents from the capped to the uncapped sector. The larger reduction target for capped firms is analogous to a smaller permit allocation. The value of the permit allocation to capped firms, $V = p_a A$, is reduced by $p_a E_{NA}$ to achieve the first best.

Therefore one should be concerned that the regulator may not be able to adjust

[24] This baseline choice eliminates any quantity of under-credited emissions reductions so that $E_{UC} = 0$. This is because no uncapped firm has BAU emissions above the assigned baseline.

[25] This is shown in the appendix. The result that the first-best solution can be achieved in the presence of asymmetric information has been established in previous work [111, 77]. Similar to the setting described in [91], the regulator requires two instruments to achieve the first-best, or one instrument per market failure.

the permit allocation to capped firms because of distributional constraints.[26] In fact, no policy to date has attempted to implement a program that would account for non-additional offsets by transferring rents across sectors. Instead of adjusting the initial permit allocation to account for non-additional offsets, the regulator can regulate the market for carbon offsets directly through a variety of alternative instruments. The use of these instruments will not be as efficient as the first-best prescription. In other words, the inability of the regulator to adjust the permit allocation puts us in a second-best setting.

We define the cost of this distributional constraint as the welfare cost per dollar of avoided transfer, which is given by the formula

$$\frac{\Delta W}{\Delta V} = \frac{W_{FB} - W_{SB}}{V_{SB} - V_{FB}}. \tag{3.13}$$

The term ΔW is defined as the non-marginal difference in welfare between first-best setting (W_{FB}) and a second-best setting (W_{SB}, when the permit allocation is fixed). The term ΔV is defined as the difference in rents to the capped sector between first- and second-best settings (V_{FB} and V_{SB}, respectively).

Moving to the second-best setting by restricting the permit allocation may lead to combinations of alternative instruments being chosen to maximize welfare. In the next sections, we provide formulae that decompose the channels of efficiency

[26]Distributional concerns have traditionally played a major role in the design of cap-and-trade programs and more generally the choice between policy instruments. As an example, distributional concerns are the primary reason that pollution permits are typically grandfathered instead of auctioned. Studies have explored how distributional constraints influence the cost effectiveness of alternative instruments [21, 22] and how grandfathered permits are necessary to keep capped firm profits unchanged [55].

by three alternative instruments: more stringent baselines, a trade ratio and a limit on the use of offsets. We refer the reader to appendix section A.2 for formal derivations.

3.2.3 The Choice of Instruments in a Second-Best Setting

The Baseline

Consider a marginal reduction of the baseline assigned to uncapped firms. The welfare effects of an incremental adjustment of the baseline are given by

$$\begin{aligned}\frac{\partial W}{\partial b} &= \underbrace{-[B'(\cdot) - p_a]\frac{\partial E_{NA}}{\partial b}}_{\mathrm{dW}^{NA}} + \underbrace{[B'(\cdot) - p_a]\frac{\partial E_{UC}}{\partial b}}_{\mathrm{dW}^{UC}} \\ &\quad + \underbrace{\int_{\underline{c}_u}^{p_f} \frac{\partial}{\partial b} \int_{\underline{e}_{u0}}^{\tilde{e}_{u0}} (p_a - c_u)(e_{u0} - \alpha) dY_u dZ_u}_{\mathrm{dW}^{A}} .\end{aligned} \tag{3.14}$$

Equation (3.14) comprises three sources of welfare change associated with a marginal reduction of the baseline. First, dW^{NA} is the *non-additional offsets effect*. This is the efficiency cost of non-additional offsets. It is equal to the product of the marginal change in non-additional offsets and the wedge between marginal benefits and marginal costs of emissions reductions of capped firms. A lower baseline implies a smaller mass of firms supplying non-additional offsets and a lower quantity of non-additional offsets awarded to uncapped firms. The lower supply of non-additional offsets can be illustrated with Figure 3.1. Areas A_4 and A_5 shrink as the baseline is adjusted down. The combined effect is a reduction in the supply of non-additional offsets. This increases capped firm compliance costs as the cap is effectively tightened when there are fewer non-additional offsets supplied. Emissions benefits are higher as a consequence of the tighter cap. These two effects are represented by the wedge between capped firm marginal benefits and marginal costs of emissions reductions.

The second component, dW^{UC}, is the *under-credited emissions reductions effect*. This is the efficiency cost of uncapped firms providing under-credited emissions reductions. It is equal to the product of the change in under-credited emissions reductions and the wedge between marginal benefits and marginal costs of emissions reductions of capped firms. A lower baseline may increase or decrease the mass of firms contributing to under-credited emissions reductions. Based on Figure 3.1, the top of area A_1 shrinks as the profit indifference line (3.7) pivots down. Simultaneously the bottom of area A_1 expands as the baseline is pushed down. An increase in under-credited emissions reductions lowers the supply of additional offsets and increases total emissions reductions. A lower supply of additional offsets increases compliance costs as fewer cheap reductions are purchased from the uncapped sector. Emissions benefits are higher as a result of greater emissions reductions. These two effects are represented by the wedge between capped firm marginal benefits and costs of emissions reductions.

The non-additional offsets effect and the under-credited emissions baseline effect influence emissions and the supply of offsets to capped firms, but do not influence the efficiency gain from allowing capped firms to pay uncapped firms to reduce emissions. This efficiency effect is captured in the last term, dW^{A}, denoted as the *additional offsets effect*. It is equal to the change in the difference between marginal costs of emissions reductions of capped and uncapped firms for the mass of uncapped firms reducing emissions. Reducing the baseline discourages the production of additional offsets as it lowers the compensation that all uncapped firms receive.

The Trade Ratio

Next consider the impact of imposing an offset trade ratio between offsets and permits, denoted by t. The trade ratio converts one offset into $\frac{1}{t}$ fungible pollution permits. A ratio greater than one implies that a capped firm must hold more than one offset to cover one unit of emissions. A major difference between a more stringent baseline and the trade ratio is that the latter cannot discourage the supply of non-additional offsets because these are defined as the difference between the baseline and BAU emissions. To decompose the welfare effects of a trade ratio, we first explore how it impacts the problem of capped firms. A trade ratio alters the permit constraint (3.2) of each capped firm to

$$a + \frac{f}{t} + a_0^i = e_r^i. \tag{3.15}$$

The first-order conditions of the capped firm problem imply

$$p_f = \frac{p_a}{t}. \tag{3.16}$$

Unlike the baseline, the trade ratio creates a wedge between the prices of offsets and permits. Holding the permit price constant, a ratio greater than one depresses the offsets price. The resulting welfare effects of adjusting the trade ratio are given by

$$\frac{\partial W}{\partial t} = \underbrace{[B'(\cdot) - p_a]f}_{\mathrm{dW}^D} + \underbrace{[B'(\cdot) - p_a]\frac{\partial E_{UC}}{\partial t}}_{\mathrm{dW}^{UC}}$$
$$+ \underbrace{\frac{\partial p_f}{\partial t}\int_{\underline{e}_{u0}}^{b}(p_a - p_f)(e_{u0} - \alpha)dY_u + \int_{\underline{c}_u}^{p_f}\frac{\partial}{\partial t}\int_{\underline{e}_{u0}}^{\tilde{e}_{u0}}(p_a - c_u)(e_{u0} - \alpha)dY_u dZ_u}_{\mathrm{dW}^A}. \tag{3.17}$$

Comparing (3.17) to (3.14) reveals three key differences between the trade ratio and the baseline. First, the trade ratio fails to exploit the non-additional offsets effect used by the baseline policy. That is, the trade ratio fails to directly discourage the production of non-additional offsets. In place of the non-additional offsets effect is the *discounted offsets effect*, denoted by dW^D.[27] This is the efficiency cost of requiring capped firms to hold more than one offset per unit of emissions. Raising the trade ratio above one reduces aggregate emissions as one unit of emissions reductions from the uncapped sector converts to less than one unit of fungible pollution permits in the capped sector.[28] Second, while adjusting the baseline has an ambiguous effect on under-credited emissions reductions, in contrast a larger trade ratio reduces under-credited emissions reductions. As a consequence, fewer under-credited emissions reductions increases overall emissions. This is captured in the second term in Equation (3.17), dW^{UC}. Third, the trade ratio discourages the opt-in decision of uncapped firms. This can be

[27]In the offsets literature, discounting offsets is equivalent to establishing a trade ratio greater than one. A discount factor of $\delta < 1$ converts one offset into δ fungible offsets. This implies an identity between an offset discount factor and an offset trade ratio: $\delta = \frac{1}{t}$. See [75] for more details.

[28]This holds true whenever there is a positive supply of additional offsets. If all offsets are non-addiitonal, then discounting will have no effect on aggregate emissions.

seen in the *additional offsets effect*, dW^A. A trade ratio larger than one reduces the offsets price below the permit price, reducing the incentive for uncapped firms to opt in, represented by the first term in dW^A. The second term is similar to the *additional offsets effect* in (3.14). It is equal to the change in the difference between marginal costs of emissions reductions of capped and uncapped firms for the mass of uncapped firms reducing emissions. Increasing the trade ratio discourages the production of additional offsets as it lowers the offset production revenue to uncapped firms.

The Offsets Limit

Finally consider a limit of L on the use of offsets by capped firms. An offsets limit adds a constraint to the capped firm problem:

$$f \leq L. \tag{3.18}$$

With this additional constraint, the capped firm first-order conditions imply a relationship between the prices:

$$p_f = p_a - \beta. \tag{3.19}$$

The term β is the multiplier on the limit constraint. A binding limit ($\beta > 0$) drives a wedge between the permit price and the offsets price.[29] For a fixed permit price, a binding limit reduces the offsets price. The offsets price is reduced until the total

[29]The Waxman-Markey bill did not provide details on the mechanism to distribute the offsets if the cap is binding. What would have most likely happened would be that each firm under the cap would be given an individual cap, similar to the way the EU-ETS has assigned separate offset limits for each country [74]. In this case if the individual caps are binding then offsets will sell at a discount relative to permits.

supply of offsets equals the limit. Like the trade ratio, this feature of the limit has the effect of reducing the supply of additional offsets while not discouraging the supply of non-addiitonal offsets.[30] This is because the supply of non-additional offsets is independent of the offsets price. The welfare effects of adjusting a binding limit are given by

$$\begin{aligned}\frac{\partial W}{\partial L} = & \underbrace{[B'(\cdot) - p_a]\frac{\partial E_{UC}}{\partial L}}_{\mathrm{dW}^{UC}} \\ & + \underbrace{\frac{\partial p_f}{\partial L}\int_{\underline{e}_{u0}}^{b}(p_a - p_f)(e_{u0} - \alpha)dY_u + \int_{\underline{c}_u}^{p_f}\frac{\partial}{\partial L}\int_{\underline{e}_{u0}}^{\tilde{e}_{u0}}(p_a - c_u)(e_{u0} - \alpha)dY_u dZ_u}_{\mathrm{dW}^{A}} .\end{aligned} \tag{3.20}$$

A comparison of (3.20) to (3.14) reveals that the limit, similar to the trade ratio, does not influence welfare through discouraging the supply of non-additional offsets as the *non-additional offsets effect* is missing. As it is the case with the previous two instruments, however, the limit influences welfare through adjusting the quantity of under-credited emissions reductions, dW^{UC}. The limit discourages uncapped firms from participating, which lowers the quantity of under-credited emissions reductions.

The second welfare effect seen in (3.20) is denoted by dW^{A}. A comparison of (3.20) to (3.17) demonstrates that the limit and the trade ratio discourage the production of additional offsets through the same two channels. In contrast to

[30]The limit can influence the supply of non-additional offsets in a setting where 100 percent of the offset supply is non-additional. In this unusual case, lowering the limit would be equivalent (in terms of total emissions) to lowering the allocation of permits to capped firms. An optimal limit will then be set to equate the marginal benefits and marginal costs of abatement in the capped sector (since no abatement will be happening in the uncapped sector).

the trade ratio, establishing a binding limit on offsets, however, unambiguously does not reduce emissions, but instead raises emissions relative to a policy with a non-binding limit. The under-credited emissions reductions effect is the only component in (3.20) that has welfare adjustments from emissions changes. A more stringent limit raises emissions because it lowers the quantity of under-credited emissions reductions and does not require capped firms to hold more offsets per unit of emissions.

3.2.6 Summary

In Table 3.1, we summarize how adjusting the instruments influences emissions and offset supply. We compare how the instruments influence the supply of non-additional offsets, the supply of additional offsets, the supply of under-credited emissions reductions and total emissions. From the welfare formulas, we see that the baseline is the only instrument that reduces the supply of non-additional offsets.[31] The trade ratio can reduce emissions if the discounted offsets effect dominates the under-credited emissions reductions effect. A more stringent offsets limit raises emissions. As the offsets limit depresses the offsets price, the quantity of under-credited emissions reductions falls, inducing an increase in total emissions.

[31] This is true unless the limit or trade ratio are selected so that there is no supply offsets, which would occur if $t = 0$ or $L = 0$.

Table 3.1: Marginal Emissions and Offset Supply Effects of the Offsets Instruments

Instrument[a]	Non-Additional Offsets	Additional Offsets	Under-Credited Emissions Reductions	Total Emissions[b]
Baseline	Decreases	Decreases	Ambiguous	Decreases
Trade ratio	No effect	Decreases	Decreases	Ambiguous
Limit	No effect	Decreases	Decreases	Increases

[a] The marginal effects represent more stringent instrument choices. We consider the marginal effect of reducing the baseline, increasing the trade ratio and reducing the limit.

[b] For the Baseline and Limit, the change in emissions is equal to the change in non-additional offset supply plus the change in under-credited emissions reductions. For the Trade Ratio, the change in emissions equals the change in non-additional offset supply, the change in under-credited emissions reductions and the change in capped firm emissions.

In Table 3.2, we sign the four effects appearing in the welfare formulas. In the first panel we consider a relaxed pre-existing cap so that marginal abatement benefits exceed marginal abatement costs. In this case, the non-additional offsets effect and the under-credited emissions reduction effect are both positive so that lowering the baseline raises social welfare through these two effects.[32] In the second panel we consider a stringent pre-existing cap so that the marginal abatement benefits are exceeded by marginal abatement costs. In this case, the three welfare effects for adjusting the baseline down are all negative, implying that the baseline should be increased at least until marginal abatement benefits equal marginal abatement costs.[33]

[32]Overall welfare may decline, however, if the welfare loss from fewer additional offsets entering the market dominates the two welfare-improving effects.

[33]This scenario is much less likely to occur in the beginning stages of cap-and-trade programs. This is because virtually all proposed and existing programs start with a relaxed cap that becomes more stringent over time.

Table 3.2: Marginal Welfare Effects of the Offsets Instruments

(a) Relaxed Pre-existing cap ($B'(\cdot) > p_a$)

Instrument	Non-Additional Offsets Effect	Additional Offsets Effect	Under-Credited Emissions Reductions Effect	Discounted Offsets Effect
Baseline	Positive	Negative	Positive	Non-existent
Trade ratio	Non-existent	Negative	Ambiguous	Positive
Limit	Non-existent	Negative	Negative	Non-existent

(b) Stringent Pre-existing cap ($B'(\cdot) < p_a$)

Instrument	Non-Additional Offsets Effect	Additional Offsets Effect	Under-Credited Emissions Reductions Effect	Discounted Offsets Effect
Baseline	Negative	Negative	Negative	Non-existent
Trade ratio	Non-existent	Negative	Ambiguous	Negative
Limit	Non-existent	Negative	Positive	Non-existent

Since the the welfare cost per dollar of avoided transfer equation (3.13) is non-marginal, we cannot assess the magnitude of welfare losses from restricting the use of the emissions cap by comparing the welfare formulas above. Therefore we rely on numerical simulations to rank the instruments along several dimensions, including the composition of offsets, total emissions, and welfare.

3.3 The Numerical Model

We now supplement the analytical model with a numerical model calibrated to represent a United States cap-and-trade program with carbon offsets. The purpose of the numerical model is to quantify exact welfare assessments in contrast with the marginal effects presented above. This is relevant for comparing the efficacy of the three instruments, providing magnitudes of the trade-offs between efficiency and rent transfers and evaluating optimal instrument choices under the second-best setting. We now provide a brief description of the model calibration procedure. A complete description of the model is available in appendix sections A.2 and A.3.

3.3.1 Model Calibration

The purpose of the numerical model is to yield generic insights that are applicable to a range of climate mitigation programs. Even though our objective is to quantify general relationships, we choose a specific set of parameter values to calibrate the model. Our central values represent abatement costs and benefits from a federal cap-and-trade program in the United States. In particular, we calibrate the analytical model with short-run (2015-2020) estimates of emission reduction costs, BAU emissions and marginal benefits of emissions reductions obtained from the literature.[34] We use short-run estimates for two reasons. First, short-run forecasts less likely to suffer from forecasting error. Second, the problem of non-additionality is most pronounced in the short run because the price of offsets is expected to be lowest in the short run.[35] To illustrate how alternative assumptions on costs and benefits may effect efficient policy decisions, we consider significant departures from these central case values in the sensitivity analysis.

The capped sector represents industries likely to be covered under a federal greenhouse gas (GHG) cap-and-trade program. We base our representation on the industries that would have been covered under the H.R. 2454 American Clean Energy and Security Act, henceforth the Waxman-Markey bill, which include coal-fired power plants, petroleum refineries, natural gas refineries, iron and steel production, cement manufacture, among others. The capped sector is regulated by a cap-and-trade program. We model the capped sector as a representative firm that takes equilibrium prices as given. This is a standard assumption used to

[34]Alternatively we can calibrate the model with medium- or long-run estimates to quantify the effects of the model for a longer time span. We leave this exercise for future work that incorporates dynamics.

[35]What we mean by the problem of non-additionality is the ratio of non-additional to additional offsets. When the price of offsets is low, the supply of additional offsets is low, making the ratio of non-additional to additional offsets large.

evaluate compliance costs of cap-and-trade programs [43]. The capped sector is allocated a fixed quantity of emissions permits that are equal to capped sector business-as-usual (BAU) emissions minus a reduction target. The uncapped sector represents major sources of mitigation that will likely not be capped in a federal climate policy. These sources include forestry and agriculture.

Data

We use estimates from the Environmental Protection Agency (EPA) analysis of Waxman-Markey of BAU emissions for the capped and uncapped sectors [36]. Capped sector marginal costs of emissions reductions are calibrated to match extrapolated values from the EPA's simulation of the Intertemporal General Equilibrium Model (IGEM) for the year 2016, while uncapped sector marginal costs of abatement are selected based on the EPA Updated Forestry and Agriculture marginal abatement cost curves [37].

Parameters

The distributions of BAU emissions and marginal costs of emissions reductions are assumed to be uniform. We calibrate the heterogeneity of BAU emissions in the uncapped sector so that the percentage of offsets that are non-additional at a carbon price of 25 dollars is 40 percent. This value approximately matches evidence from the largest carbon offsets program in the world, the Clean Development Mechanism. The marginal benefits of emissions reductions, known as the Social Cost of Carbon (SCC), is set at 25 dollars per ton of CO_2 equivalent, representing estimated damages between 2015-2020 [39]. Table 3.3 summarizes the values used to calibrate the model and Table 3.4 shows implied parameter values. The calibrated model approximately matches the predicted compliance cost savings from including offsets in the Waxman-Markey cap-and-trade program. Section A.3 provides more details on the calibration procedure and data used to identify the parameters of the model.

Table 3.3: Benchmark Data

Description	Value	Source
Capped sector BAU emissions[a]	5,071	EPA Data Annex (2009)
Uncapped sector BAU emissions	365	EPA MAC Curves (2009)
Capped sector emissions reductions	864	EPA Data Annex (2010)
Uncapped sector emissions reductions	486	EPA MAC Curves (2009)
Uncapped sector sequestration potential	1,027	EPA MAC Curves (2009)
Percent of offsets that are non-additional[b]	40	Schneider (2007)
Social cost of carbon[c]	25	EPA Technical Support Document (2010)

[a] Emissions are reported in million metric tons of CO_2 equivalent.
[b] Equal to the quantity of non-additional offsets divided by total offset supply at a baseline equal to the expected value of uncapped firm BAU emissions.
[c] Represents an estimate for the year 2016 and is reported in (year 2000) dollars per ton of CO_2 equivalent.

Table 3.4: Implied Parameter Values

Parameter description	Parameter	Value
Capped sector lower bound of marginal costs[a]	$\underline{c}_r$	0
Uncapped sector lower bound of marginal costs	$\underline{c}_u$	0
Capped sector upper bound of marginal costs	$\overline{c}_r$	147
Uncapped sector upper bound of marginal costs	$\overline{c}_u$	72
Capped sector average BAU emissions[b]	$\mathbb{E}(e_{r0})$	$5,071$
Uncapped sector average BAU emissions	$\mathbb{E}(e_{u0})$	365
Capped sector lower bound of BAU emissions	$\underline{e}_{r0}$	$5,071$
Uncapped sector lower bound of BAU emissions	$\underline{e}_{u0}$	-563
Capped firms upper bound of BAU emissions	$\overline{e}_{r0}$	$5,071$
Uncapped sector upper bound of BAU emissions	$\overline{e}_{u0}$	$1,293$

[a] Marginal costs are reported as (year 2000) dollars per ton of CO_2 equivalent.
[b] Emissions are reported as million metric tons of CO_2 equivalent.

3.3.2 Numerical Results

This section presents results from the numerical model. To compare the offsets instruments, we calculate the welfare effect of imposing an emissions cap under different assumptions on the set of instruments available to the policy maker. We emphasize the welfare effects relative to a series of benchmark settings that we consider in the next section.

To facilitate comparisons, we simulate the model without offsets as a benchmark. Our emphasis is on qualitative, rather than quantitative, differences across policies. The quantitative differences can vary depending on our assumptions for marginal abatement costs and benefits and the heterogeneity in uncapped firm BAU emissions. Note that our analysis abstracts from other sources of emissions changes that may plague offsets markets, including leakage and permanence.[36]

Benchmark Simulations

We first examine benchmark simulations that help facilitate comparisons of the three offsets instruments. Table 3.5 presents simulation results for our benchmark settings. The first setting represents a cap-and-trade program that does not include offsets. Under this setting, the allocation of permits is endogenously chosen to maximize welfare. Welfare - defined as emission reduction benefits

[36]While leakage and permanence may have relevant impacts on the welfare effects of offsets programs, we do not focus on them in our paper. Previous literature suggests that liability and insurance or buffering programs are superior instruments for handling leakage and permanence [93].

minus costs - is 10.8 billion dollars.[37]

[37] The implied emissions price from the case without offsets is equal to the social cost of carbon.

Table 3.5: Welfare and Rents Under Benchmark Settings

	No Offsets	Full Information[a]		Imperfect Information[b]	
Permits	*Optimal*	*No Offsets setting*	*Optimal*	*No Offsets setting*	*Optimal*
Baselines	–	*Firm-specific*	*Firm-specific*	*Mean*	*Optimal*
Welfare[c]	10,800	+36 %	+56 %	+15 %	+56 %
Costs	10,800	-36 %	+56 %	-62 %	+56 %
Benefits	21,600	0 %	+56 %	-23 %	+56 %
Cost per ton of emissions reductions[d]	12.5	8.0	12.5	6.2	12.5
Capped Sector Rents[e]	105,170	67,310	93,024	54,827	69,815

[a] Defined by the policy maker observing uncapped firm-specific BAU emissions. Under this setting, baselines are set equal to BAU emissions so that the supply of non-additional offsets and the quantity of under-credited emissions reductions equals zero.

[b] Defined by the policy maker observing the distribution of uncapped firm BAU emissions. Under this setting, a common baseline is set for all uncapped firms.

[c] Reported in millions of dollars in the No offsets setting. Values in the Full Information and Imperfect Information settings are reported relative to the No Offsets setting.

[d] Measured in dollars per ton of CO_2 equivalent.

[e] Reported in millions of dollars and defined as the product of the capped sector permit allocation and the equilibrium permit price.

Next we simulate the model assuming that the policy maker has full information on BAU emissions. Under this assumption, the policy maker assigns baselines equal to BAU emissions of uncapped firms, $b^i = e^i_{u0}$. In these simulations, adverse selection is not present and only additional offsets are awarded to the uncapped sector and supplied to capped firms. When the allocation of permits remains at the no offsets optimum, including offsets increases welfare by 36 percent. The welfare change is attributed to a reduction in compliance costs, as cheaper reductions from the uncapped sector replace more expensive reductions in the capped sector. When the cap is re-optimized when offsets are included, the welfare change increases to 56 percent. This increase represents the first-best allocation of emission reductions.

The next set of simulations assumes that the policy maker has imperfect information on BAU emissions. These settings represent the numerical version of our analytical model. With imperfect information, the policy maker assigns a single baseline to each uncapped firm. We consider two benchmark cases in the presence of imperfect information. First, we consider the case where the allocation of permits equal the no offsets optimum and the baseline equals the expected value of BAU emissions. This setting achieves a 15 percent increase in welfare relative to the no offsets program, a value which is significantly lower than the full information settings. This is because adverse selection is present. Firms in areas A_4 and A_5 are supplying non-additional offsets, which increases aggregate emissions and lowers the benefits from the program. Second, we consider the case where the policy maker can select both the allocation of permits and the baseline. With both instruments, the policy maker can achieve the first best outcome. The increase in welfare of 56 percent matches the welfare change in the full information setting that allows the policy maker to re-optimize the permit allocation. Comparing capped sector rents across the settings, however, demonstrates the distributional consequence of the imperfect information first-best outcome. Capped sector rents in the imperfect information first-best outcome are 69.8 billion dollars compared to 105.2 billion dollars in the no offsets case. While the first-best solution achieves a significant increase in welfare, along with it comes a rent transfer equal to roughly 30 percent of rents under the no offsets setting.

Instrument choice

In the analytical model, we consider one instrument at a time to isolate key welfare effects. In the numerical model we consider the welfare implications of allowing the regulator to choose the instruments simultaneously. This allows us to determine whether some instruments may be coupled together to achieve higher welfare gains relative to cases when instruments are optimized one by one. Moreover, we determine whether some instruments welfare-dominate others by restricting them one at a time.

Table 3.6 shows optimal instrument choices under different assumptions on the policy maker instrument choice set. Without offsets, the optimal allocation of permits is $4,207$ MMTCO$_2$e.[38] The remaining settings include offsets in the

[38]In this table we report the average cost of emissions reductions (total cost divided by total

case when the regulator has imperfect information on BAU emissions. To achieve the first best under imperfect information, the baseline is set equal to the upper bound of BAU emissions ($b = \overline{e}_{u0}$) and the permit allocation is adjusted down to account for the supply of non-additional offsets. The trade ratio and the limit are not utilized to achieve the first best.

emissions reductions) equal to 12.5/tCO2e.

Table 3.6: Instrument Choice

	No Offsets	First Best	Second Best[a] Unrestricted	Baseline	Ratio	Limit
Permits	*Optimal*	*Optimal*	*No offsets setting*	*No offsets setting*	*No offsets setting*	*No offsets setting*
Value[b]	4,207	2,793	4,207	4,207	4,207	4,207
Baseline	–	*Optimal*	*Optimal*	*Optimal*	*Mean*	*Mean*
Value[b]	–	1,293	-447	-229	365	365
Trade Ratio	–	*Optimal*	*Optimal*	*Restricted Optimal*[c]	*Optimal*	*1:1 ratio*
Value	–	1	0.67	1	1.78	1
Limit	–	*Optimal*	*Optimal*	*Optimal*	*Optimal*	*Optimal*
Value	–	Non-binding	Non-binding	Non-binding	Non-binding	Non-binding

[a] Defined as fixing the permit allocation equal to 4,207 $MMTCO_2e$.
[b] Measured in million metric tons of CO_2 equivalent.
[c] The restricted optimal setting is defined by the policy maker selecting the baseline, trade ratio and limit subject to the constraint $t \geq 1$.

Next we simulate the model under four second-best settings that are characterized by an exogenous permit allocation set equal to the No Offsets optimum. First, we simulate the model when the baseline, trade ratio and limit are selected simultaneously by the policy maker. We label this scenario as Unrestricted. Importantly - and surprisingly - the policy maker finds it optimal to couple a trade ratio less than one with a low baseline. This finding is robust to different parameter assumptions, as confirmed in the sensitivity analysis below.[39] From the first-order condition of the capped firm problem, a trade ratio less than one has the effect of increasing the offsets price. A higher offsets price encourages a larger supply of additional offsets and a larger quantity of under-credited emissions reductions. The policy maker simultaneously adjusts the baseline down to reduce the supply of non-additional offsets. This increases welfare through the non-additional offsets effect as greater emissions reductions are achieved. Adjusting the baseline down, however, reduces the welfare gains from the additional offsets effect as fewer uncapped firms find it profitable to opt in. A trade ratio less than one counteracts this effect by boosting up the offsets price. This leads to a welfare gain that is represented by the additional offsets effect in Equation (3.17).

In practice, however, it is unlikely for a policy to adopt a trade ratio less than one.[40] In addition to the effects described above, a trade ratio less than

[39]This can be seen in Table 3.12 by focusing on the column labeled Unrestricted.

[40]We are not aware of an offsets program that uses a trade ratio less than one. A recent survey of environmental offsets programs finds that there do not exist programs assigning a trade ratio less than one [62].

one allows capped firms to turn one offset into more than one fungible pollution permit. If not coupled with another instrument that lowers emissions, this has the effect of raising aggregate emissions.[41] For this reason, we consider a setting that allows the policy maker to select the three instruments simultaneously with the constraint that the trade ratio cannot be below one, $t \geq 1$. We label this policy as "Baseline" since we find that in this setting, only the baseline is utilized. The optimal baseline in this setting is equal to -229 $MMTCO_2e$, a value that is larger (e.g. more generous) than the one from the previous setting. This is because the policy maker can no longer encourage the production of additional offsets by selecting a trade ratio less than one. The optimal trade ratio of one implies that it is not used as a method of reducing emissions. A ratio larger than one can reduce emissions but it also reduces the incentive for uncapped firms to opt in and it distorts the decision for uncapped firms to reduce emissions. While adjusting the baseline down also discourages uncapped firms from opting in, it does not distort the decision for uncapped firms to reduce emissions as it does not directly reduce the offsets price. This difference is represented by the term in the additional offsets effect appearing in Equation (3.17) that is absent in Equation (3.14).

To compare the efficacy of the trade ratio and the limit, we remove the baseline from the policy maker's choice set and assume that it is exogenously set to equal the expected value of uncapped firm BAU emissions. In this setting, the second-best trade ratio equals 1.78, requiring capped firms to buy 1.78 offsets to

[41]For example, the policy maker could lower the permit allocation to capped firms or create under-credited emissions reductions with a lower baseline.

account for one unit of emissions. The limit remains non-binding in this case, demonstrating that on welfare grounds, the trade ratio is a superior instrument. This is because the trade ratio and limit both discourage under-credited emissions reductions and the supply of additional offsets through the same mechanism - through a reduced offsets price. But the trade ratio can reduce emissions while the limit cannot. In fact, there is no analog to the discounted offsets effect in the limit welfare formula.

To determine whether the limit is binding under any circumstances, we restrict the baseline and the trade ratio to be fixed and allow the policy maker to select a limit that maximizes welfare. The limit does not bind in this case. This suggests that the limit cannot improve welfare in the presence of adverse selection.[42]

Composition of Offsets and Emissions

Table 3.7 compares the quantity of additional and non-additional offsets and the sources of emissions reductions for each of the simulation settings. In the first-best outcome, the supply of non-additional offsets is significant. Out of the total offset supply of $1,414$ MMTCO$_2$e, 928 MMTCO$_2$e are non-additional. These

[42]The result that the optimal policy suggests a non-binding limit begs the question of why offset limits offsets exist at all. Some programs that have limits explicitly state in its design summary that offsets are suppose to be "supplemental" to emission reductions taking place among capped firms [74]. This preference for supplementary reductions may stem from three reasons: First, it may be that policy makers are worried that not all offsets are additional, so that a limit restricts the potential increase in emissions. Second, it may be an ethical concern. Constituents may feel that polluters should not be able to depend on other uncapped firms to reduce emissions for them. Third, uncertain abatement costs with increasing cap stringency over time with unlimited offset quantities may keep permit prices below levels sufficient to induce investment in low-emission technologies or curb demand for high emission products [42, 34]. We thank a referee for pointing out this third possibility.

offsets come from the first-best instrument choice of the baseline set high enough to encourage all uncapped firms to opt in. At this baseline choice, every uncapped firm earns some non-additional offsets since BAU emissions are below each firm's baseline.

Table 3.7: Composition of Offsets and Emissions

	No Offsets	First Best	Second Best			
			Unrestricted	Baseline	Ratio	Limit
Capped sector emissions reductions[a]	864	864	684	699	650	450
Uncapped sector emissions reductions	0	486	237	217	171	211
Under-credited emissions reductions	0	0	120	81	24	30
Additional offsets	0	486	117	136	162	181
Non-additional offsets	0	928	4	29	233	233
Offset supply	0	1,414	121	165	395	414
Capped sector emissions	4,207	4,207	4,388	4,372	4,421	4,621
Uncapped sector emissions	365	-121	128	148	193	154
Total emissions[b]	4,572	4,086	4,515	4,520	4,614	4,775

[a] Emission reductions, offsets and emissions quantities are measured in million metric tons of CO_2 equivalent.

[b] Total emissions are defined as the sum of capped and uncapped sector emissions.

In the Unrestricted policy, non-additional offsets are close to zero. This is because the non-additional offsets effect dominates the additional offsets effect at the second-best optimal policy. The efficient baseline choice is so low in this setting that very few non-additional offsets are awarded to uncapped firms. Surprisingly, total emissions are lower in the Unrestricted setting relative to setting when offsets are not allowed. This is because the quantity of under-credited emissions reductions equal to 120 MMTCO_2e has the effect of lowering aggregate emissions. This effect dominates the increase in emissions from the supply of non-additional offsets and from a trade ratio less than one.

Under the Baseline policy, additional and non-additional offset supply are both higher than they appear in the Unrestricted policy. The Baseline policy sets a higher baseline to uncapped firms to encourage the supply of additional offsets. This also raises the supply of non-additional offsets from 4 MMTCO_2e to 29 MMTCO_2e. under-credited emissions reductions fall to 81 MMTCO_2e because the price of offsets is not boosted by a trade ratio less than one.

The Ratio and Limit policies show a substantially larger supply of non-additional offsets of 233 MMTCO_2e. This is because neither of these instruments are capable of reducing the supply of non-additional offsets. As a consequence, we see a much larger supply of offsets and higher aggregate emissions.

Second-Best Welfare

We now consider the welfare impacts – emission reduction benefits less economic costs – of the different policies. Table 3.8 presents the welfare impacts of the four second-best policies relative to a program that does not include offsets. The Unrestricted policy achieves the greatest welfare gain that is 35 percent greater than the welfare impact of a program without offsets. We see that under this policy that emission reduction benefits are 7 percent greater than the no offsets policy. This is because under-credited emissions reductions exceed the supply of non-additional offsets and the extra emissions from a trade ratio less than one (see Table 3.7).

Table 3.8: Second-Best Welfare

	No Offsets	Second Best			
		Unrestricted	Baseline	Ratio	Limit
Welfare[a]	10,800	+35 %	+34 %	+26 %	+15 %
Costs	10,800	-21 %	-22 %	-36 %	-62 %
Benefits	21,600	+7 %	+6 %	-5 %	-23 %

[a] Reported in millions of dollars in the No offsets setting. Values in the Second Best settings are reported relative to the No Offsets setting.

The same effect holds true for the Baseline policy which achieves an increase in benefits of 6 percent. The Baseline policy increases welfare by 34 percent, a value that is slightly less than the Unrestricted policy. This small difference suggests that the combination of the discounted offsets effect and the additional offsets is small. The additional efficiency gains from encouraging greater participation of uncapped firms through a higher offsets price just barely exceeds the welfare losses from higher emissions.

The Ratio and Limit policies achieve an increase in welfare that is smaller than the efficiency gains from the Unrestricted and Baseline policies. This result is driven by the absence of the non-additional offsets effect in the trade ratio and limit formulas. Since neither instrument can discourage the supply of non-additional offsets, benefits dramatically fall under these settings by 5 percent and 23 percent, respectively. The Ratio policy achieves a higher welfare gain compared to the Limit policy because of the discounted offsets effect. This effect increases benefits by effectively lowering emissions via requiring capped firms to hold more than one offset to cover one unit of emissions. Even though the trade ratio discourages the supply of additional offsets and achieves a smaller cost reduction of 36 percent, the discounted offsets effect more than compensates for this as the welfare gain under the Ratio policy is 11 percentage points higher than the welfare gain under the Limit policy.

Distributional Concerns

We now examine the distributional consequences of the policies in Table 3.9.

Moving from a program that does not include offsets to the first-best outcome, we see a large reduction in capped sector rents from $105,170$ million dollars to $69,815$ million dollars. Under most of the second-best settings, however, the reduction in rents is smaller.

Table 3.9: Distributional Effects

	No Offsets	First Best	Second Best Unrestricted	Baseline	Ratio	Limit
Capped sector rents[a]	105,170	69,815	83,334	85,046	79,183	54,827
Permit price[b]	25.00	25.00	19.81	20.22	18.82	13.03
Welfare change[c]	6,075	–	2,331	2,421	3,227	4,455
Avoided transfer[d]	35,335	–	13,519	15,231	9,368	-14,988
Welfare cost per unit of avoided transfer[e]	0.17	–	0.17	0.16	0.34	-0.30

[a] Reported in millions of dollars.
[b] Reported in dollars.
[c] Defined by subtracting the welfare in the current setting from the First-Best welfare. Reported in millions of dollars.
[d] Defined by subtracting the capped sector rents in the First-Best setting from the current setting. Reported in millions of dollars.
[e] Defined as the ratio of the welfare change and the avoided transfer.

To evaluate the distributional formula (3.13), we calculate two terms: First, we require the difference between first-best welfare and the welfare from the particular policy. We denote this value in Table 3.9 as Welfare Change. The welfare change is the largest when offsets are not included in the program ($6,075$ million dollars) since all of the cheaper reductions from uncapped firms are not realized. The Unrestricted and Baseline policies achieve the lowest welfare loss of $2,331$ and $2,421$ million dollars, respectively. This is because these policies are able to encourage uncapped firms to opt in and reduce emissions. Second, we compute the avoided transfer of rents, which is defined as the quantity of capped sector rents in a particular policy minus the capped sector rents under the first-best solution. The avoided transfer is the largest under the no offsets setting ($35,335$ million dollars). The avoided transfers are lower under the second-best settings because the permit price is depressed from the existence of offsets.

The Baseline policy achieves a welfare cost per unit of avoided transfer of 0.16. This value is lower than the marginal excess burden of a labor tax of 0.40 dollars [60]. If the regulator had to choose among the policy options of sacrificing 0.16 dollars in welfare to avoid one dollar of transfers or allowing the rent transfer to take place but compensate capped firms through revenues generated from a labor tax, they should choose the former as it is less costly per dollar of transfers.

The welfare cost per unit of avoided transfer is substantially lower than the marginal excess burden. This follows from the fact that the rent transfer is significantly larger than the welfare gain stemming from the first-best mechanism.

This result can be explained by illustrating the first-best mechanism using Figure 3.1. The first-best requires moving the baseline b up to $b = \bar{e}$ so that all projects opt in. There are two sources of rent transfer from this action. First, projects that would have opted in without the first-best implemented now are awarded a significantly larger quantity of non-additional offsets that they sell to the capped sector. These projects are represented by areas A_3, A_4 and A_5. Second, projects that would not have opted in without the first-best mechanism now opt in and sell non-additional offsets. These projects are represented by areas A_1 and A_2. Therefore every eligible project sells a significant quantity of non-additional offsets under the first-best outcome. The rent transfer occurs to counter-act the emissions consequences of these offsets as the policy maker reduces the allocation of permits by an amount that is equal to the new quantity of non-additional offsets.

The welfare gain from the first-best mechanism comes from encouraging projects that can cheaply reduce emissions that otherwise would not have opted in. These projects appear in area A_1. The welfare gain from the first-best mechanism will be a function of the cost-effectiveness of these projects relative to the most expensive abatement occurring in the capped sector. This welfare gain is likely to be substantially less than the rent transfer associated with implementing the first best because of two reasons. First, most projects that have cheap mitigation costs would already opt in without the first-best implemented (areas A_3 and the left of A_4). Second, the size of A_1 is most likely a small fraction of the universe of eligible projects (areas $A_1 - A_5$). Since this result may depend on policy design parameters that we use in our central case, in the next section we investigate various alternative assumptions to test its sensitivity.

3.4 Further Analysis

3.4.1 Alternative Baselines

Thus far we have focused on a setting where a policy maker has access to all three offsets instruments. In some emissions trading programs, however, it may be the case that baselines are set independently from the choice of the trade ratio or the limit. This feature motivated our consideration of treating the baseline as exogenous to the policy maker under the Ratio and Limit policies. Under these policies, however, we considered a baseline set to equal the expected value of BAU emissions. Some baseline protocols could, in practice, call for higher or lower baselines, depending on the stringency of the offset standard. To consider how different baselines influence outcomes for welfare and rent transfers, we simulate the model assuming alternative baselines. In particular we set the baseline equal to 50 percent and 200 percent of the expected value of BAU emissions. The results appear in Table 3.10. The Low Baseline and High Baseline settings are simulated with a baseline set to equal 50 percent and 200 percent of the expected value of BAU emissions, respectively. For the Low Baseline case, the optimal trade ratio is now only 1.45. The policy maker does not need to set a stringent trade ratio in this case because the baseline has already been set low. The same intuition applies to the high baseline case. Here we see a higher trade ratio of 2.69 to account for a large supply of non-additional offsets.

Table 3.10: Alternative Baselines

	Low Baseline ($b = 0.5\mathbb{E}(e_{0u})$)		High Baseline ($b = 2\mathbb{E}(e_{0u})$)	
Ratio	*Optimal*	*1:1 ratio*	*Optimal*	*1:1 ratio*
Value	1.45	1	2.69	1
Limit	*Optimal*	*Optimal*	*Optimal*	*Optimal*
Value	Non-binding	Non-binding	Non-binding	0
Offset supply[a]	304	331	571	0
Additional offsets	155	182	121	0
Non-Additional offsets	149	149	450	0
Under-credited emissions reductions	38	45	7	0
Welfare[b]	13,980	13,491	12,920	10,800
Costs	7,209	5,494	6,565	10,800
Benefits	21,189	18,985	19,485	21,600
Capped sector rents	79,705	64,721	79,307	105,170

[a] Offset supplies and emission reductions are reported in million metric tons of CO_2 equivalent.

[b] Welfare, costs, benefits and rents are reported in millions of dollars.

In contrast to our results above, we find that it is optimal to place a limit of zero in the High baseline case. For a high baseline, the efficiency losses from higher emissions dominate the efficiency gains from including offsets in the program.[43] Therefore the optimal limit of zero is equivalent to not allowing offsets into the program. As long as marginal benefits from abatement exceed marginal costs, the optimal policy is to set the offsets limit to zero.[44]

3.4.2 Transaction Costs

Several studies have documented that transaction costs associated with the production of carbon offsets can be non-trivial [8, 47]. We evaluate the impact of transaction costs on the efficacy of the instruments considered by adding a 5 dollar per ton of offsets produced.[45] We assign transaction costs to offset projects in line with an analysis of Waxman-Markey by the Congressional Budget Office [71]. This value lies within a range of transaction costs estimated in previous work.[46]

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[43] The reverse holds true if the exogenous cap is very stringent. This is because under a stringent cap ($B?() < p_a$) allowing extra non-additional offsets into the program improves welfare (see Table3.2).

[44] Our model does not include other market failures besides the emissions externality and the information asymmetry. When additional failures exist, such as the adoption of new technology, binding limits my be optimal as shown in [34].

[45] Denoting the per unit transaction cost by t, the profit function of an uncapped firm becomes

$$\pi^i = \max_{\alpha \le e_u^i \le e_{u0}^i} \left\{ (p_f - t)(b - e_u^i) - c_u^i(e_{u0}^i - e_u^i) \right\}. \tag{3.21}$$

[46] For example, Antinori and Sathaye compute transaction costs for 26 carbon offset projects around the world [8]. Their survey includes a variety of offset project types, including forestry, energy efficiency, fuel switching, fuel capture, and renewables. These projects operated between 1991 and 2005 and were verified and monitored through different offset protocols, including the CDM, the Chicago Climate Exchange and Climate Trust. The authors find that transaction costs

We simulate the model with a 5 dollar per ton transaction cost and calculate the optimal set of instruments. Our results appear in Table 3.11. We see two results emerge from the simulations. First, transaction costs do not play a role in determining the relative efficacy of the three instruments. This result is illustrated by comparing Table 3.6 to the top panel of Table 3.11. For example, under the baseline policy, it is always optimal to set a stringent baseline but keep the trade ratio equal to one. Second, the existence of transaction costs dramatically reduces the welfare cost per unit of avoided transfer across all of the policies, which is reported in the last row of Table 3.11. For the unrestricted and baseline second-best policies, the cost is less than five cents per dollar of avoided transfer. The reason that these values are significantly smaller than those we find in a model without transaction costs stems from the fact that a transaction cost essentially shifts the price curve in Figure 1 to the left, which reduces the area A_1. This is the mass of uncapped firms that bring efficiency gains from the first-best mechanism. Since the efficiency gains will be less with higher transaction costs, the sacrifice in welfare when moving to the second-best policies will be lower.

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per ton of CO_2 for the surveyed projects fall within the range of 0.03 per ton of CO_2 and 4.05 per ton of CO_2 with an average of 0.36 per ton of CO_2. Galik et al. estimate transaction costs for US-based forest carbon offset projects [47]. The authors used a detailed spreadsheet model that includes dis-aggregated forest types and 10 different regions. For all project types, transaction costs are estimated to be less than 25 percent of median implementation costs, which the authors define as the sum of production costs and transaction costs. We follow the CBOs approach by assigning a 5 dollar per ton of CO_2 to all projects as this value represents a central value to those reported in existing studies.

Table 3.11: Transaction Costs[a]

	First Best	Second Best			
		Unrestricted	Baseline	Ratio	Limit
Baseline	*Optimal*	*Optimal*	*Optimal*	*Mean*	*Mean*
Value	1,293	-563	-351	365	365
Ratio	*Optimal*	*Optimal*	*Restricted Optimal*	*Optimal*	*1:1 ratio*
Value	1	0.50	1	1.68	1
Limit	*Optimal*	*Optimal*	*Optimal*	*Optimal*	*Optimal*
Value	Non-binding	Non-binding	Non-binding	Non-binding	Non-binding
Offset supply[b]	1,352	91	100	323	365
Additional offsets	424	91	88	90	132
Non-Additional offsets	928	0	12	233	233
Under-credited emissions reductions	0	135	7	15	22
Transaction costs[c]	6,761	453	501	1,617	1,820
Welfare	14,179	13,926	13,364	12,621	12,094
Costs[d]	14,848	8,461	9,693	6,829	4,242
Benefits	30,241	22,827	23,058	19,449	16,336
Capped sector rents	69,815	84,540	92,969	81,780	60,870
$\Delta W/\Delta V$	–	0.02	0.04	0.13	-0.23

[a] The simulations presented in this table include a per ton of CO_2 offset transaction cost of 5 dollars.
[b] Offset supplies and emission reductions are reported in million metric tons of CO_2 equivalent.
[c] Transaction costs, welfare, costs, benefits and rents are reported in millions of dollars.
[d] Costs are equal to mitigation costs plus transaction costs.

3.4.3 Further Sensitivity Analysis

Table 3.12 summarizes the sensitivity of the numerical results to a range of values for relevant parameters. We vary the social cost of carbon, the upper bound of the marginal cost of emissions reductions distributions for the capped and uncapped sectors and the benchmark percentage of offsets that are non-additional.[47] Table 3.12 displays for different parameter values the optimal instrument choices and the welfare cost per unit of avoided transfer ($\Delta W/\Delta V$).

[47] Adjusting down the upper bound of the marginal cost distribution for uncapped firms represents allowing more offset types into the program, which could potentially include international offsets.

Table 3.12: Further Sensitivity Analysis

			No Offsets	First Best	Second Best			
					Unrestricted	Baseline	Ratio	Limit
Social Cost of Carbon	40	Permits[a]	3,689	1,984	3,689	3,689	3,689	3,689
		Baseline	–	1,293	-295	-162	365	365
		Trade Ratio	–	1	0.82	1	1.52	1
		$\Delta W/\Delta V$	0.23	–	0.16	0.16	0.22	1.07
	10	Permits	4,725	3,362	4,725	4,725	4,725	4,725
		Baseline	–	1,293	-563	-345	365	365
		Trade Ratio	–	1	0.54	1	3.28	1
		$\Delta W/\Delta V$	0.09	–	0.23	0.12	0.55	-0.07
Capped Sector Upper Bound of Marginal Costs	172	Permits	4,334	2,920	4,334	4,334	4,334	4,334
		Baseline	–	1,293	-484	-263	365	365
		Trade Ratio	–	1	0.65	1	1.92	1
		$\Delta W/\Delta V$	0.17	–	0.22	0.19	0.47	-0.22
	122	Permits	4,032	2,695	4,032	4,032	4,032	4,032
		Baseline	–	1,293	-403	-190	365	365
		Trade Ratio	–	1	0.69	1	1.64	1
		$\Delta W/\Delta V$	0.18	–	0.16	0.15	0.30	-0.45
Uncapped Sector Upper Bound of Marginal Costs	97	Permits	4,207	3,112	4,207	4,207	4,207	4,207
		Baseline	–	1,101	-371	-152	365	365
		Trade Ratio	–	1	0.68	1	1.63	1
		$\Delta W/\Delta V$	0.16	–	0.17	0.14	0.54	-0.19
	47	Permits	4,207	2,222	4,207	4,207	4,207	4,207
		Baseline	–	1,620	-465	-327	365	365
		Trade Ratio	–	1	0.77	1	2.01	1
		$\Delta W/\Delta V$	0.19	–	0.21	0.19	0.28	-0.67
Benchmark Percentage of Non-Additional Offsets	60 %	Permits	4,207	2,123	4,207	4,207	4,207	4,207
		Baseline	–	1,959	-583	-386	365	365
		Trade Ratio	–	1	0.65	1	2.35	1
		$\Delta W/\Delta V$	0.12	–	0.12	0.12	0.16	-0.69
	20 %	Permits	4,207	3,302	4,207	4,207	4,207	4,207
		Baseline	–	784	-294	-154	365	365
		Trade Ratio	–	1	0.8	1	1.63	1
		$\Delta W/\Delta V$	0.21	–	0.33	0.26	0.66	-0.21

Two features of the model explain the relationship between the SCC and optimal instrument choice. First, the higher the SCC, the lower the quantity of allowances allocated to capped firms.[48] Second, the optimal quantity of allowances and the stringency of offsets instruments move in opposite directions.[49] The lower the quantity of allowances, the more lenient the optimal offset policy becomes.[50] This will generally be the case in the second-best settings as well. When the quantity of allowances is low, emissions are low and permit and offset prices are high. Therefore the policy may be getting too many emissions reductions. In response the policy maker can relax the stringency on offset projects by raising baselines or removing the non-unitary trade ratio. When the social cost of carbon is low (SCC = 10), the optimal permit allocation without offsets is high ($A = 4,725$). In the Baseline Policy case, the baseline is set to -365. When the social cost of carbon is high (SCC = 40), the optimal cap without offsets is low ($A = 3,689$). In the Baseline policy, the baseline is set to -162, which is much more lenient than the case when the cap is high.

When the SCC is high, the welfare cost per unit of avoided transfer lies below 0.40 for all of the policies with the exception of the limit policy.[51] The cap is more stringent in this setting, leading to high equilibrium permit and offset prices. As a consequence, the share of offsets that are non-additional is lower since more

[48] This is because we set the exogenous quantity of allowances to the point that equalizes marginal abatement benefits and marginal abatement costs without offsets.

[49] The quantity of allowances are reported as Permits in Table 3.12.

[50] Recall that in the first-best policy prescription, the cap is lowered and baselines to uncapped firms are made more generous.

[51] Recent estimates suggest that the social cost of carbon will rise to 45 dollars in the year 2050 under a three percent discount rate [39].

projects find it profitable to opt in and reduce emissions. Therefore the welfare cost of the second best policies is not large relative to the rent transfer.

The results appear to be insensitive to adjusting the upper bound of the marginal cost of emissions reductions distribution for the capped and uncapped sectors. Optimal instrument choices move in intuitive directions as we adjust the bounds of the uncapped sector marginal cost distribution. A higher upper bound for the uncapped sector marginal cost distribution encourages the policy maker to relax the stringency of the offsets instruments in the second-best settings. A higher upper bound for the capped sector marginal cost distribution suggests that the policy maker sets more stringent instrument choices. This occurs as a response to a less stringent exogenous permit allocation.

Our simulation results are sensitive on our assumption for the benchmark level of non-additional offsets. This level is related to the heterogeneity in uncapped project BAU emissions, where a greater amount of heterogeneity implies a larger fraction of non-additional offsets. In this section we vary the parameter values that set the level of heterogeneity to determine how the share of offsets that are non-additional influence our results. In the fourth panel of Table 3.12 we vary the benchmark share of non-additional offsets between two extreme cases: 20 percent and 60 percent. The 20 percent case represents a program that sets stringent additionality standards while the 60 percent case more closely resembles a program with relaxed standards.[52]

[52]There exist many types of offset standards for each project type, with some that have more stringent application and verification requirements than others. (See [76] for an excellent survey

Changing the benchmark percentage of offsets that are non-additional has a significant impact on the welfare cost per unit of avoided transfer. When the benchmark percentage is low, the cost is high because capped firm rents in the first-best setting are not much lower than they are in the second-best settings. This occurs because the baseline does not need to be adjusted up very much to encourage all uncapped firms to opt in, requiring a smaller reduction in permits to capped firms to account for the supply of non-additional offsets. Under either benchmark percentage, however, the cost per unit of avoided transfer remains below the marginal excess burden of 0.40.

of the most popular standards.) The Waxman-Markey bill did not explicitly state that type of standard that would be used to set baselines and verify offsets, so it is uncertain how stringent the offset policy would have been.

CHAPTER 4

ON THE IMPORTANCE OF BASELINE SETTING IN MARKETS FOR CARBON OFFSETS

4.1 Introduction

Complementing cap-and-trade programs with carbon offsets supplied from uncapped sectors is recognized as a way of achieving emissions reduction targets at lower economic cost [26, 30, 81, 10, 118]. However, awarding offsets to projects requires the setting of a baseline that reflects the project's BAU emissions. Offsets are counted based on documented emissions relative to baselines. If the offset project managers have more information on the project's BAU emissions than the regulator that assigns the project baseline, then the program may attract projects that have baselines above their BAU emissions. Managers opt in these projects into the program and can claim offsets up to their baseline while not reducing emissions [88, 87, 97, 45]. When these offsets are sold to firms regulated under a cap-and-trade program, overall emissions in the economy can increase [72, 50, 106, 122].

The issue at hand is one of crediting of emissions reductions. A program may award a project with offsets that exceeds the project's emissions reductions, leading to the production of offsets that we define as *over-credited offsets*. But the crediting system may also lead to emissions reductions that do not generate offsets. A project is under-credited with a quantity of offsets that is less than the project's emissions reductions. This happens when a project is assigned a baseline below its BAU emissions. These projects lower emissions more than the quantity of offsets they earn and can reduce aggregate emissions by the difference between the project's baseline and its predicted BAU emissions. We call the reduction in aggregate emissions *under-credited emissions reductions*. While such reductions have been identified as a source that can counter-act the emissions consequences of over-credited offsets [106, 48, 49], little is known about the relative importance of over-credited offsets and under-credited emissions reductions for different levels of baseline stringency and carbon prices.

4.2 Analytical Framework of Carbon Offset Supply

We developed a framework of carbon offset supply within a cap-and-trade program to measure the importance of under-credited emissions reductions and over-credited offsets and to examine the overall emissions under different levels of baseline stringency and carbon prices. A key feature of the framework is that that there are information asymmetries between the regulator that assigns baselines and project managers. Economists have long studied the challenges of designing policies in markets with imperfect information [121, 33, 77, 111]. Closely related to our work is a strand of economics literature that examines adverse selection issues that arise in SO_2 tradeable permit markets [90, 91], incentives to reduce emissions from deforestation [116], design payments for environmental services [44] and sectoral crediting of voluntary emissions reductions [89]. Some of these studies focus on the unintended effects of over-crediting and conclude that there exists an undesirable trade-off between reductions in the compliance costs of cap-and-trade programs and increases in aggregate emissions. Other studies recognize the emissions benefits under-credited emissions reductions but do not model the magnitude of these reductions relative to over-credited offsets [107, 48, 49]. By modeling both of these effects, we find that incorporating offsets into cap-and-trade programs can actually reduce the overall compliance costs of theses programs while maintaining emissions caps, provided baselines are set sufficiently stringent. We show that the emissions effects of under-credited emissions reductions can fully compensate for the unintended increases in emissions from over-credited offsets, especially when carbon prices have achieved higher values.

The framework developed here assumed that whether a project generates offsets depends on six variables: its BAU emissions, u_i, its sequestration potential, s_i, its marginal costs of mitigation, c_i, its assigned baseline, b_i, its per ton transaction cost, t_i and the per-ton price of offsets, p. Given these, each project manager can calculate the profitability of reducing emissions sufficiently to generate offsets, and the optimal level of offset supply. In Figure 4.1, we divide approved projects into different categories based on project characteristics (see the appendix for a derivation of Figure 4.1). Project i's BAU emissions, u_i, is shown on the horizontal axis while its marginal costs of mitigation, c_i, is on the vertical axis.

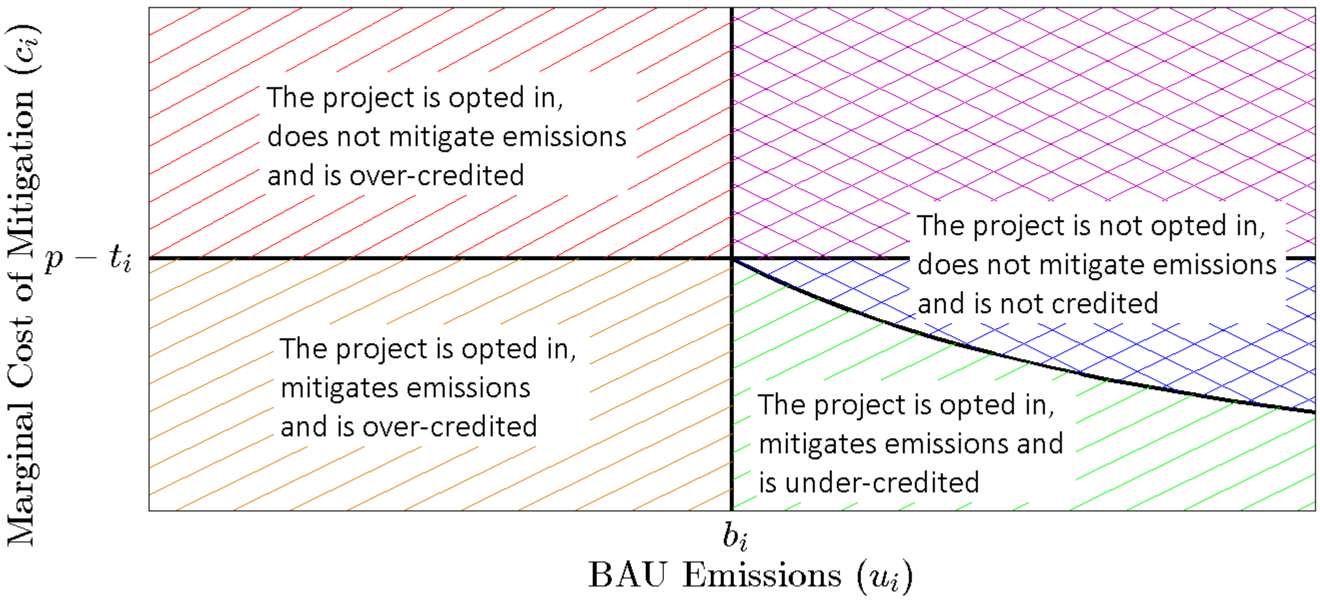


Figure 4.1: Opt In Decisions of Potential Projects.

The manager of an approved project can either commence with the project (i.e. opt in into the program) or decide not to start the project (i.e. does not opt in). Approved projects that have either high marginal costs of mitigation or relatively low baselines are not profitable enough for the manager to opt in. These are designated by the purple and blue cross-hashed regions in Figure 4.1. There are some projects that are profitable enough for the manager to opt in and have its project perform mitigation but are under-credited because they are assigned a baseline below their BAU emissions. These are projects that fall into the green region and are characterized by marginal costs of mitigation that are sufficiently below the offsets price less transaction costs. Managers of projects that are assigned a baseline above the project's BAU emissions opt in their project and are over-credited. These projects fall into the red region of Figure 4.1 and would have commenced without the program taking place. This is because these projects have marginal costs of mitigation above the offsets price less transaction costs. The orange region in Figure 4.1 includes projects that perform mitigation but are over-credited. These projects would not have occurred in the absence of the program, since their marginal costs of mitigation fall below the offsets price less transaction costs. However, they are awarded a greater quantity of offsets than the quantity of emissions reductions they provide. In this case, the projects earn some offsets that correspond to mitigation and some that do not correspond to mitigation (e.g. over-credited offsets). When regulated sectors under a cap-and-trade program can use offsets to meet the cap, the supply of over-credited offsets lead to overall emissions increases while under-credited emissions reductions lead to overall emissions reductions. While under-credited emissions reductions are critically affected by the price of offsets, over-credited offsets are not (see the appendix for an illustration of this effect).

4.3 Numerical Simulations

We coupled our framework with numerical simulations to yield some generic insights applicable to future carbon offset programs. Although we attempt to convey general conclusions, we commit our analysis to specific parameters in simulating the model. Our central case values for the parameters that influence offset supply decisions are based on United States offset supply data, although they can easily be generalized to include international offsets (see the appendix for a description of the data and model calibration). The simulations are calibrated to represent emissions reductions targets and offset supply proposed under the 2009 Waxman-Markey legislation. This bill would have allowed regulated sources to meet up to one billion tons of their compliance obligation with purchases of domestic offsets. Our simulations quantify how large under-credited emissions reductions are relative to over-credited offsets for different levels of baseline stringency and carbon prices.

We discovered that for a range of parameter values, under-credited emissions reductions exceed the supply of over-credited offsets if baselines are set stringent enough. Figure 4.2 shows the composition of offsets and emissions changes for a range of baselines on the horizontal axis, expressed as a proportion of predicted BAU emissions. A proportion less than one implies that every project's baseline is less than its predicted BAU emissions. The vertical axis measures offset supply and emissions changes in terms of million metric tons of CO_2 equivalent ($MMTCO_2e$).

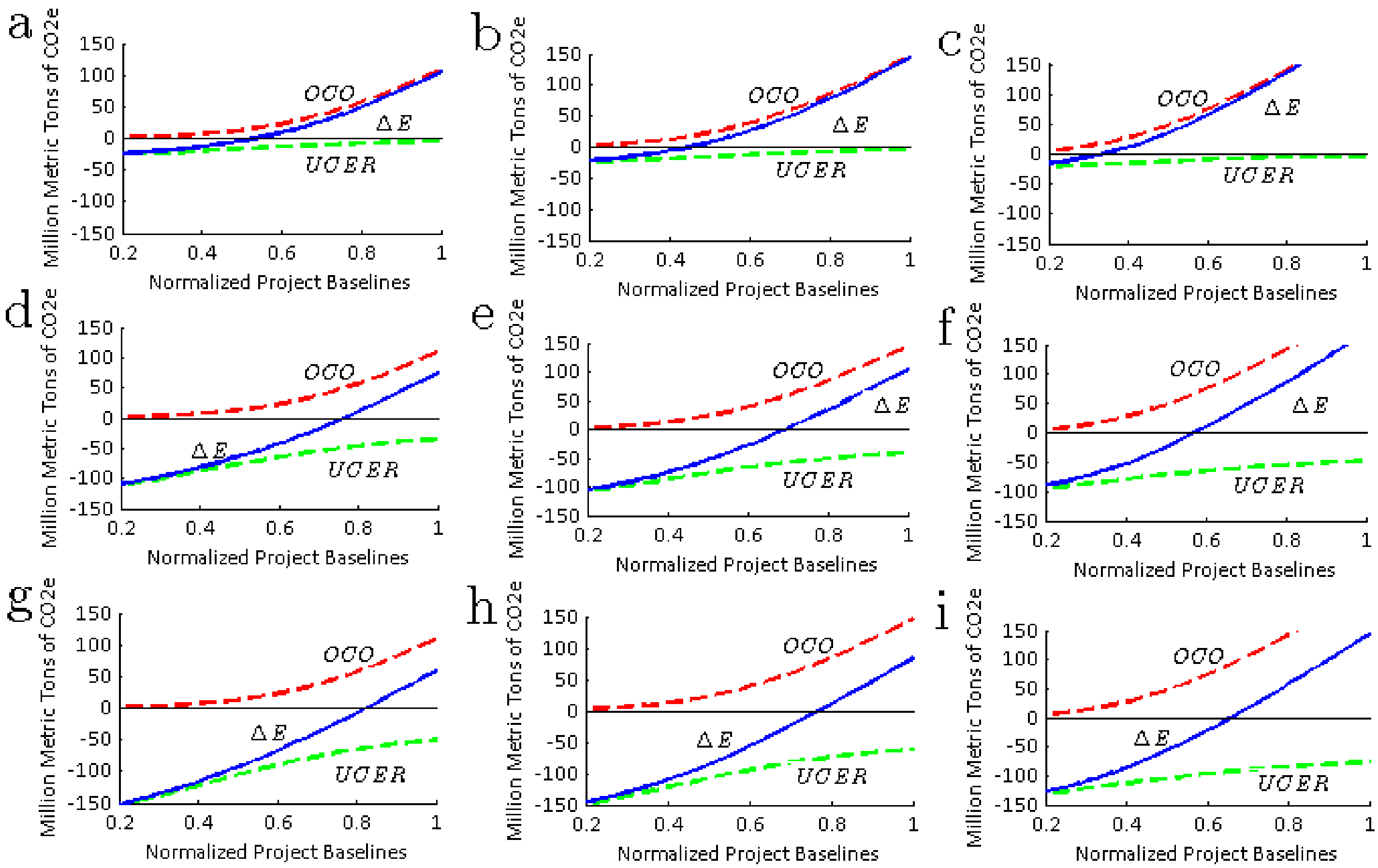


Figure 4.2: Aggregate Change in Emissions as a Function of Baseline Stringency

The different curves show outcomes for the supply of over-credited offsets (OCO), aggregate change in emissions (ΔE), and under-credited emissions reductions ($UCER$). The aggregate change in emissions is relative to a program that does not include offsets. If the capped sector reduction target is high and when baselines are set to be less than 60 percent predicted BAU emissions, under-credited emissions reductions exceed the supply of over-credited offsets (Figure 4.2 g,h,i). For this range of baselines, emissions decrease. A higher reduction target yields a higher equilibrium offsets price, which encourages greater participation by project developers as the marginal returns to mitigating emissions is higher. Therefore it is more likely for managers of projects with assigned baselines less than their BAU emissions to opt in. This increases the quantity of under-credited emissions reductions while having no effect on the supply of over-credited offsets. When the degree of uncertainty on BAU emissions is low (Figure 4.2 2g), less stringent baselines are necessary for aggregate emissions to fall. Low BAU emissions uncertainty implies that a project is more likely to receive a baseline that matches its BAU emissions. This has the effect of reducing the supply of over-credited offsets since there will be fewer projects that have baselines above their BAU emissions.

If the degree of uncertainty for predicted BAU emissions is high, it is less likely for the quantity of under-credited emissions reductions to exceed the supply of over-credited offsets (Figure 4.2 c,f,i). A higher degree of uncertainty implies that projects have more extreme predicted BAU emissions. A project that has predicted BAU emissions that are substantially larger than its BAU emissions is more likely to receive a baseline that exceeds its BAU emissions. The manager of this project will likely opt in and earn over-credited offsets. On the other hand, a project that has predicted BAU emissions that are substantially lower than its BAU emissions is more likely to receive a baseline so low that it its manager will no longer find it profitable to opt in its project. In this case, the project does not generate under-credited emissions reductions. When the capped sector reduction target is low (Figure 4.2 c), this effect is amplified as project managers have a lower revenue incentive to opt in their project and have it mitigate emissions. In this case, project baselines must be very stringent – less than 35 percent of predicted BAU emissions – for the quantity of under-credited emissions reductions to exceed the supply of over-credited offsets. For a capped sector reduction target of $2,000$ MMTCO$_2$e and the benchmark level of uncertainty (Figure 4.2 e), the net effect on emissions of creating an offsets market is zero when baselines equal 70 percent of predicted BAU emissions.

Our analysis thus far suggests that the emissions consequences of under-credited emissions reductions can potentially cancel the emissions consequences from the supply of over-credited offsets if baselines are stringent. Setting baselines low, however, may eliminate a significant supply of offsets and lead to lost opportunities [114]. This could potentially reduce much of the cost savings from including offsets in cap-and-trade programs. To determine the relationship between baseline stringencies, offset supply and cost savings, we simulate the model under three baseline protocols. We define the protocol denoted by 'Predicted BAU Emissions' by setting baselines equal to predicted BAU emissions. We call the the second protocol 'Minimize Supply of Over-Credited Offsets'. This protocol sets baselines to ensure that there is no supply of over-credited offsets. The third protocol, 'Maintain Environmental Integrity', adjusts baselines to the point where the aggregate supply of over-credited offsets equals the quantity of under-credited emissions reductions. Under this protocol, the effect of including offsets in the cap-and-trade program has no net effect on emissions as the two sources of emissions changes cancel.

Table 4.1 reports offsets supply and emissions consequences of including offsets in the cap-and-trade program for three capped sector reduction targets. Panels (a), (b) and (c) report estimates for a low (short run), medium and high (long run) capped sector reduction target, respectively. In general, the higher the reduction target, the higher the equilibrium price of permits and offsets. This result is illustrated by comparing the equilibrium offset prices across the three panels. When the capped sector reduction target is low, equilibrium prices range from 7.66 to 11.69 dollars, while with a high capped sector reduction target, equilibrium prices range from 75.86 to 85.85 dollars.

Table 4.1: The effect of alternative baseline protocols on offset supply and emissions

(a) Capped Sector Reduction Target = 500 $MMTCO_2e$	Predicted BAU Emissions	Minimize Supply of Over-Credited Offsets	Maintain Environmental Integrity
Baselines	$b_i = \tilde{u}_i$	$b_i = 0$	$b_i = 0.46\tilde{u}_i$
Offset Price	7.66	11.69	10.57
Percentage of projects opting in	51	7	23
Total Offset Supply	202	86	127
Exact Offsets	58	86	109
Over-Credited Offsets	144	0	17
Under-Credited Emissions Reductions	4	27	17
Total Change in Emissions	140	−27	0
(b) Capped Sector Reduction Target = 2,000 $MMTCO_2e$	**Predicted BAU Emissions**	**Minimize Supply of Over-Credited Offsets**	**Maintain Environmental Integrity**
Baselines	$b_i = \tilde{u}_i$	$b_i = 0$	$b_i = 0.70\tilde{u}_i$
Offsets Price	38.14	47.02	40.83
Percentage of projects opting in	66	30	57
Total Offset Supply	652	338	556
Exact Offsets	505	338	497
Over-Credited Offsets	147	0	59
Under-Credited Emissions Reductions	40	112	59
Total Change in Emissions	107	−112	0
(c) Capped Sector Reduction Target = 3,500 $MMTCO_2e$	**Predicted BAU Emissions**	**Minimize Supply of Over-Credited Offsets**	**Maintain Environmental Integrity**
Baselines	$b_i = \tilde{u}_i$	$b_i = 0$	$b_i = 0.77\tilde{u}_i$
Offsets Price	75.86	85.85	78.43
Percentage of projects opting in	74	39	68
Total Offset Supply	817	436	728
Exact Offsets	672	436	653
Over-Credited Offsets	147	0	75
Under-Credited Emissions Reductions	61	152	75
Total Change in Emissions	86	−152	0

Carbon offset prices are reported in dollars per ton of CO_2e. Offset supply, emissions reductions and changes in emissions are reported in $MMTCO_2e$.

Table 4.1 highlights three key findings. First, setting baselines equal to predicted BAU emissions leads to a substantial increase in emissions. For a low capped sector reduction target (Table 4.1, Panel (a)), there are only 4 $MMTCO_2e$ under-credited emissions reductions, compared to 144 $MMTCO_2e$ over-credited offsets, leading to an aggregate increase in emissions of 140 $MMTCO_2e$. Emissions increase because projects with baselines above their BAU emissions opt in and receive over-credited offsets, while projects with baselines below their BAU emissions are not as likely to opt in and generate under-credited emissions reductions. Second, baseline protocols that attempt to fully eliminate the supply of over-credited offsets significantly reduce the supply of offsets. Across all three capped sector reduction target scenarios, we find that the minimize supply of over-credited offsets protocol has a much lower supply of offsets than the predicted BAU emissions protocol. For a capped sector reduction target of $2,000$ $MMTCO_2e$, total offset supply is about 50 percent less under the minimize supply of over-credited offsets protocol. Third, the maintaining environmental integrity baseline protocol does not significantly reduce the supply of offsets as long as offset prices are high. For a capped sector reduction target of $3,500$ $MMTCO_2e$, total offset supply under the maintain environmental integrity protocol is 728 $MMTCO_2e$, which is only ten percent less than total offset supply under the predicted BAU emissions protocol. High offset prices encourage greater fraction of projects with baselines set below their BAU emissions. Greater participation by these projects increase the quantity of under-credited emissions reductions. As a consequence, as the equilibrium offsets price increases, there is less need for setting stringent baselines to balance the supply of over-credited offsets and the quantity of under-credited emissions reductions. This feature is illustrated by recognizing the required baseline stringencies for the different equilibrium offset prices. While low offset prices require very stringent baselines (Table 4.1, Panel (a), $b_i = 0.46u_i$), high offset prices provide room for leeway (Table 4.1, Panel (c), $b_i = 0.77u_i$). Moving from a short-run cap of 500 MMTCO$_2$e to a medium run cap of 2,000 MMTCO$_2$e – which corresponds to moving from the year 2018 reduction target to the year 2026 reduction target under Waxman-Markey – allows the policy to relax baseline stringencies by 50 percent. This suggests that for a one dollar increase in the equilibrium offsets price, baselines can be increased by between one to two percent to maintain the environmental integrity of the program.

Table 4.2 translates offset supply and equilibrium prices from Table 4.2 into cost savings estimates from including offsets in the cap-and-trade program. We find that the protocol that minimizes the supply of over-credited offsets severely reduces the cost savings from incorporating offsets into the program. For a capped sector reduction target of 2,000 MMTCO$_2$e, cost savings are over 50 percent less relative to the predicted BAU emissions protocol (Table 4.2, Panel (b)). In contrast, the maintain environmental integrity protocol does not sacrifice much cost savings as long as the capped sector reduction target is sufficiently high. When the target is set to 3,500 MMTCO$_2$e, cost savings are only about 10 percent less relative to the predicted BAU emissions protocol. This result stems from the fact that more stringent reduction targets generate a supply of offsets that are only slightly less under the maintain environmental integrity protocol (Table 4.1). The result suggests that the trade-off between environmental integrity and compliance cost savings is insignificant under aggressive emissions reduction targets.

Table 4.2: The cost savings from including offsets in cap-and-trade programs under alternative baseline protocols

(a) Capped Sector Reduction Target = 500 $MMTCO_2e$	No Offsets	Predicted BAU Emissions	Minimize Supply of Over-Credited Offsets	Maint. Env. Integrity
Capped Sector Mitigation	500	272	413	373
Offset Supply	0	204	86	127
Capped Sector Mitigation Costs	3,538	1,048	2,420	1,969
Uncapped Sector Mitigation Costs	0	101	314	340
Uncapped Sector Transaction Costs	0	1,019	430	636
Total Compliance Costs	3,538	2,169	3,164	2,946
Cost Savings	–	1,369	374	592

(b) Capped Sector Reduction Target = 2,000 $MMTCO_2e$	No Offsets	Predicted BAU Emissions	Minimize Supply of Over-Credited Offsets	Maint. Env. Integrity
Capped Sector Mitigation	2,000	1,350	1,661	1,442
Offset Supply	0	650	339	557
Capped Sector Mitigation Costs	56,600	25,784	39,020	29,419
Uncapped Sector Mitigation Costs	0	7,172	6,034	7,524
Uncapped Sector Transaction Costs	0	3,249	1,697	2,785
Total Compliance Costs	56,600	36,206	46,751	39,728
Cost Savings	–	20,394	9,849	16,872

(c) Capped Sector Reduction Target = 3,500 $MMTCO_2e$	No Offsets	Predicted BAU Emissions	Minimize Supply of Over-Credited Offsets	Maint. Env. Integrity
Capped Sector Mitigation	3,500	2,678	3,031	2,769
Offset Supply	0	817	434	730
Capped Sector Mitigation Costs	173,338	101,488	130,022	108,499
Uncapped Sector Mitigation Costs	0	15,036	11,507	15,115
Uncapped Sector Transaction Costs	0	4,084	2,168	3,649
Total Compliance Costs	173,338	120,608	143,698	127,263
Cost Savings	–	52,730	29,640	46,075

Capped and uncapped sector mitigation are reported in $MMTCO_2e$. Costs and cost savings estimates are reported in millions of (year 2000) dollars.

4.4 Implications of the Framework for Instrument and Project Choice in Carbon Offset Programs

Concerns about the impact of over-credited offsets on total emissions have led to the development and use of other policy instruments such as trade ratios or offset limits [74]. Under a trade ratio, regulated firms must forgo more than one ton of offsets to account for one ton of their own emissions. Under a limit, regulated firms are limited in the total amount of offsets they can use to meet the cap. The framework developed here suggests that the use of these instruments, however, is problematic. A trade ratio effectively lowers the offsets price and, as a consequence, cannot affect the supply of over-credited offsets. At the same time, a lower offsets price reduces the profitability of offsets projects. This has the undesired effect of lowering the quantity of under-credited emissions reductions as fewer managers of projects that perform mitigation opt in their project. Similarly, the use of limits on the quantity of offsets use by the capped sector cannot lower emissions because it will simply lower the equilibrium price of offsets, and thus again reduce the participation of offsets projects and the quantity of under-credited emissions reductions.

Our framework also serves as a guide to policy makers for determining whether certain project types should be included and when different project types are likely to lead to increases in aggregate emissions. We link our framework to evidence from prior studies on BAU emissions uncertainty, marginal costs of mitigation, potential offset supply and transaction costs to provide prescriptions on which offset project types policy makers may find desirable (see appendix). For example, our framework suggests that projects that have low marginal costs of mitigation, including HFC-23 destruction and N2O abatement, are likely to dramatically lower compliance costs without jeopardizing environmental integrity as they provide cheap mitigation and large quantities of under-credited emissions reductions.

In addition to the significant cost reductions that offsets bring, recent arguments for including them in cap-and-trade programs point to the importance of their co-benefits. For example, offsets may be worthwhile for their ability to encourage the development of adaptation and transition toward a low-carbon world [32]. Other experience with carbon offsetting suggests that programs can prevent biodiversity loss and serve as a payment for ecosystem services projects [109, 57, 69]. The additional non-GHG mitigation benefits may be valuable enough to warrant incorporating offsets in cap-and-trade programs even when over-credited offsets exceed under-credited emissions reductions. Baselines calculated here can be further relaxed to account for these additional co-benefits.

4.5 Methods

Our simulation model includes an uncapped sector that is comprised of heterogeneous projects and a capped sector represented by a single cost-minimizing firm. We assign values for the mitigation cost parameters based on estimates used in the EPA's analysis of Waxman-Markey, including the curvature of the uncapped sector marginal cost of mitigation function [37], proposed emissions reduction targets for Waxman-Markey [36], and the predicted costs of capped sector mitigation [36]. We calibrate the degree of uncertainty in uncapped project BAU emissions based on a meta-analysis on the proportion of historical offset supply that does not correspond to mitigation [105].

Offsets are supplied by projects in the uncapped sector. For each capped sector reduction target that we consider, we assume that a quantity of emissions permits is grandfathered to the regulated firms that equals regulated firm BAU emissions minus the reduction target. While others have pointed to other allocation methods for these types of systems [55], whether permits are grandfathered or auctioned does not change our conclusions but instead influences the distribution of rents among firms and the regulator. The capped sector complies with the program by holding permits, reducing emissions through abatement or buying offsets. Permit and offset prices are solved endogenously so that the demand for permits and offsets by capped firms equals the supply of permits by the regulator and the supply of offsets from projects, respectively. For full details see the appendix.

The Supply of Offsets

Project managers respond to an endogenous offsets price determined in equilibrium and the baseline set by the regulator. The change in emissions calculations are relative to a cap-and-trade program that prohibits a capped sector from using offsets for compliance.

We model the managerial decisions of projects to supply offsets through a project-specific profit function:

$$\pi_i = \max_{s_i \le e_i \le u_i} \left\{ (p - t_i)(b_i - e_i) - c_i(u_i - e_i) \right\}. \tag{4.1}$$

Supply decisions by project managers are based on six variables: BAU emissions (u_i), sequestration potential (s_i), a marginal cost of mitigation (c_i) an assigned emissions baseline (b_i), a per unit transaction cost (t_i) and the price of offsets that is common to all projects (p). The manager of project i knows with certainty its project's BAU emissions, while the regulator only knows predicted BAU emissions, which equal project-specific BAU emissions plus a project-specific emissions shock. Baselines are set as a function of predicted BAU emissions. Ex-post emissions are assumed to be common knowledge that the policy maker can perfectly observe. The emissions shocks are independently and identically drawn from a normal distribution with mean zero and standard deviation equal to the expected value of BAU emissions. This yields an expected quantity of over-credited offsets equal to 30 percent of total offset supply when baselines are set to equal predicted BAU emissions in an equilibrium with a carbon price of 25 dollars per ton of CO_2. This value is consistent with survey data on the proportion of total offset supply that is non-additional [105].

Each manager's decision whether to opt in its project and whether to mitigate is based on (4.1). Project managers compare the profits of the different decisions and choose the combination that yields the highest profit. Managerial decisions yield offset supply and under-credited emissions reductions, which are used to calculate the change in emissions. We assume that project managers face a 5 dollar per ton transactions cost when deciding to opt their project into the program. We consider alternative assumptions about transaction costs and find that higher costs generally reduce under-credited emissions reductions relative to over-credited offsets.

We generate the supply of offsets and emissions effects with a simulation calibrated to United States emissions and mitigation cost data. We exclude a supply of international offsets in our benchmark simulations because of the high level of uncertainty in existing estimates for this supply. Our sensitivity analysis, however, includes scenarios that incorporate a supply of non-U.S. offsets. We assume that there are $1,000$ potential domestic projects that are capable of GHG mitigation. The distribution of marginal costs of mitigation is calibrated to match EPA forecasts of mitigation cost curves for the United States forestry and agriculture sector [37].

For each iteration of the simulation, we generate data by drawing from the defined distributions of each characteristic for all of the $1,000$ projects. The projects then make profit-maximizing decisions, which lead to a supply of offsets, under-credited emissions reductions and emissions changes. We perform $2,000$ iterations of this procedure to obtain an expected value for each of the key outputs.

The Capped Sector

Offsets are supplied to the capped sector that must comply with an emissions reduction target. We model the capped sector as a representative firm, an assumption that is consistent with prior literature [43, 42]. We calibrate the abatement cost structure of the capped sector with processed simulation output from the EPA's analysis of the Waxman-Markey bill [36]. The capped sector emissions reduction target translates into a fixed supply of emissions permits. The capped sector must hold one emissions permit or one offset for every unit of emissions that it does not mitigate. The permit and offset prices are determined endogenously through the market-clearing condition that the supply and demand for each commodity are equal. We consider a wide range of capped sector emissions reduction targets, with a central case of a medium run target of $2,000$ MMTCO$_2$e. This is the predicted required abatement for the year 2026 in the Waxman-Markey bill.

Sensitivity Analysis

Given these assumptions, we vary the tightness of offset project baselines, from 20 percent to 100 percent of predicted BAU emissions, and analyze the pattern of offset supply and emissions changes stemming from the quantity of under-credited emissions reductions and the supply of over-credited offsets. Sensitivity analysis around the basic assumptions including the standard deviation of BAU emissions shocks, the offset mitigation supply curve, the correlation between key variables, systematic bias in predicting BAU emissions and different measures of transaction costs is reported in the appendix. In each section of sensitivity analysis, we report the ratio of under-credited emissions reductions to over-credited offsets, offset supplies for broad ranges of the parameters and how different offset protocols affect the cost savings from including offsets in cap-and-trade programs. Tables B.9 report key model outputs for scenarios when a larger supply of offsets is allowed into the program, which represents a setting with international offsets. In these simulations we assume that the supply of mitigation function is multiplied by a constant proportion. We consider a wide range of alternative scenarios, including 25 percent (expensive mitigation opportunities) and 400 percent (cheap mitigation opportunities). Values above 100 percent represent cases where there are cheaper mitigation opportunities, e.g. when the program incorporates international offsets. When there are cheaper mitigation opportunities from offsets projects, there will be a greater quantity of under-credited emissions reductions created, implying that baselines can be made less stringent to insure the environmental integrity of the program.

APPENDIX A

APPENDIX FOR *DESIGNING EFFICIENT MARKETS FOR CARBON OFFSETS WITH DISTRIBUTIONAL CONSTRAINTS*

A.1 Introduction

This appendix includes derivations of the key equations provided throughout the paper, provides details on the calibration procedure used to simulate the model and a model validation exercise. In Section A.2, we derive all of the relevant equations and welfare formulas that require proof. In Section A.3, we explain and provide documentation for the calibration procedure we use to set parameters for the simulation model. Section A.4 includes a validation exercise where we compare the predictions of our model to simulation results of Waxman-Markey as reported by the EPA.

A.2 The Analytical Model

A.2.1 Deriving condition (3.3)

The Lagrangian of the capped firm problem defined by (3.1)-(3.2) is

$$L = p_a a^i + p_f f^i + c^i(e^i_{r0} - e^i_r) + \lambda(a^i + a^i_0 + f^i - e^i_r) + \mu_{e1} e^i_r + \mu_{e2}(e^i_{r0} - e^i_r) + \mu_a(a^i + a^i_0) + \mu_f f^i. \quad \text{(A.1)}$$

The first-order conditions for the two choice variables are

$$p_a + \lambda, \tag{A.2}$$

$$p_f + \lambda. \tag{A.3}$$

Combining (A.2) and (A.3) yields (3.3).

A.2.2 Derivation of the first-best instrument choice

To achieve the first best, the regulator chooses a reduction target and a baseline to maximize (3.12) subject to (3.8)-(3.11). Differentiating (3.12) with respect to the reduction target $\overline{q}$ and setting to zero yields

$$B'(\cdot) = C_r'(\cdot). \tag{A.4}$$

By the definition of a well-functioning permit market, we have that $B'(\cdot) = C_r(\cdot) = p_a$.[1] Differentiating (3.12) with respect to the baseline and setting to zero gives

$$\frac{\partial W}{\partial b} = -[B'(\cdot)-p_a]\frac{\partial E_{NA}}{\partial b}+[B'(\cdot)-p_a]\frac{\partial E_{UC}}{\partial b}+\frac{\partial}{\partial b}\int\limits_{\underline{c}_u}^{p_f}\int\limits_{\underline{e}_{u0}}^{\tilde{e}_{u0}}(p_a-c_u)(e_u-\alpha)dY_u dZ_u = 0. \tag{A.5}$$

Substituting (A.4) into (A.5) defines efficient baseline choice:

$$\frac{\partial W}{\partial b} = \frac{\partial}{\partial b}\int\limits_{\underline{c}_u}^{p_f}\int\limits_{\underline{e}_{u0}}^{\tilde{e}_{u0}}(p_f - c_u)(e_u - \alpha)dY_u dZ_u = 0. \tag{A.6}$$

The condition requires that the baseline be adjusted to the point where there does not exist a wedge between marginal costs of emissions reductions for the capped

[1] The proof of this appears in the next section of the appendix.

and uncapped sectors. The condition is met when the regulator sets the baseline equal to the upper bound of the unconstrained emissions distribution, $b = \overline{e}_{u0}$. With this instrument choice, all uncapped firms opt in. Moreover, there is a significant quantity of non-additional offsets, E_{NA}. To achieve the first best, the regulator increases the reduction target $\overline{q}$ from q^* to $q^* + E_{NA}$,where q^* would have been the reduction target had all offsets been additional.

A.2.3 Proof of $C_r'(\cdot) = p_a$

Define compliance costs for the capped sector, $C_r(q_r)$, as

$$C_r(q_r) = \int_{\underline{c}_r}^{p_a(q_r)} \int_{\underline{e}_{r0}}^{\overline{e}_{r0}} c_r e_{r0} dY_r dZ_r, \tag{A.7}$$

where q_r denotes the equilibrium quantity of abatement by the sector:

$$q_r = \int_{\underline{c}_r}^{p_a} \int_{\underline{e}_{r0}}^{\overline{e}_{r0}} e_{r0} dY_r dZ_r. \tag{A.8}$$

Assuming that the relationship between q_r and p_a is monotonic,[2] we can invert (A.8) to define the inverse function $p_a(q_r)$ that appears in (A.7). Differentiating (A.7) with respect to q_r yields

$$\frac{dC_r}{dq_r} = \int_{\underline{e}_r}^{\overline{e}_{r0}} e_{r0} dY_r \frac{dp_a}{dq_r} p_a(q_r). \tag{A.9}$$

[2]This is essentially putting restrictions on the distributions of BAU emissions and compliance costs such that the supply of abatement is upward-sloping.

Differentiating (A.8) with respect to p_a yields

$$\frac{dq_r}{dp_a} = \int_{\underline{e}_{r0}}^{\bar{e}_{r0}} e_{r0} dY_r. \tag{A.10}$$

Substituting (A.10) into (A.9) and canceling like terms yields

$$\frac{dC_r}{dq_r} = p_a(q_r). \tag{A.11}$$

A.2.4 Deriving Equation (3.14)

Differentiating Equation (3.12) with respect to the baseline yields

$$\frac{\partial W}{\partial b} = -B'(\cdot)\left(\frac{\partial E_{NA}}{\partial b} - \frac{\partial E_{UC}}{\partial b}\right) + C_r'(\cdot)\left(\frac{\partial E_{NA}}{\partial b} - \frac{\partial E_{UC}}{\partial b}\right) - C_r'(\cdot)\frac{\partial q_u}{\partial b} - \frac{\partial C_u}{\partial b}. \tag{A.12}$$

Substituting $p_a = C_r'(\cdot)$ and combining like terms gives

$$\frac{\partial W}{\partial b} = [p_a - B'(\cdot)]\left(\frac{\partial E_{NA}}{\partial b} - \frac{\partial E_{UC}}{\partial b}\right) - C_r'(\cdot)\frac{\partial q_u}{\partial b} - \frac{\partial C_u}{\partial b}, \tag{A.13}$$

which can be expressed as

$$\frac{\partial W}{\partial b} = [p_a - B'(\cdot)]\left(\frac{\partial E_{NA}}{\partial b} - \frac{\partial E_{UC}}{\partial b}\right) + \frac{\partial}{\partial b}\int_{\underline{c}_u}^{p_f}\int_{\underline{e}_{u0}}^{\tilde{e}_{u0}} (p_a - c)(e_{u0} - \alpha) dY_u dZ_u. \tag{A.14}$$

Expressing the first term as benefits minus costs gives

$$\frac{\partial W}{\partial b} = -[B'(\cdot) - p_a]\left(\frac{\partial E_{NA}}{\partial b} - \frac{\partial E_{UC}}{\partial b}\right) + \frac{\partial}{\partial b}\int_{\underline{c}_u}^{p_f}\int_{\underline{e}_{u0}}^{\tilde{e}_{u0}} (p_a - c_u)(e_{u0} - \alpha) dY_u dZ_u. \tag{A.15}$$

Carrying the differential in the second term yields Equation (3.14).

A.2.5 Deriving Equation (3.16)

The Lagrangian of the capped firm problem defined by (3.1), (3.2) and (3.15) is

$$L = p_a a^i + p_f f^i + c^i(e^i_{r0} - e^i_r) + \lambda\left(a^i + a^i_0 + \frac{f^i}{t} - e^i_r\right) + \mu_{e1} e^i_r + \mu_{e2}(e^i_{r0} - e^i_r) + \mu_a(a^i + a^i_0) + \mu_f f^i. \tag{A.16}$$

Assuming that the firm makes offsets and permit purchases, the first-order conditions are

$$p_a + \lambda, \tag{A.17}$$

$$p_f + \frac{\lambda}{t}. \tag{A.18}$$

Combining (A.17) and (A.18) yields (3.16).

A.2.6 Deriving Equation (3.17)

Welfare with a trade ratio is

$$W = B\left[\overline{q} - E_{NA} + E_{UC} + \left(1 - \frac{1}{t}\right)f\right] - C_r\left(\overline{q} - \frac{f}{t}\right) - C_u, \tag{A.19}$$

where $f = E_{NA} + q_u - E_{UC}$ is the supply of offsets. Differentiating (A.19) with respect to the trade ratio gives

$$\frac{\partial W}{\partial t} = B'(\cdot)\frac{\partial E_{UC}}{\partial t} + B'(\cdot)\frac{\partial}{\partial t}\left[\left(1 - \frac{1}{t}\right)f\right] + C_r'(\cdot)\frac{\partial}{\partial t}\left(\frac{f}{t}\right) - \frac{\partial C_u}{\partial t}. \tag{A.20}$$

Evaluating the derivatives and substituting in the expression for f gives

$$\begin{aligned}\frac{\partial W}{\partial t} =& B'(\cdot)\frac{\partial E_{UC}}{\partial t} - B'(\cdot)\left[\frac{\partial E_{UC}}{\partial t}\left(1 - \frac{1}{t}\right) + \frac{\partial q_u}{\partial t}\left(1 - \frac{1}{t}\right) + \frac{f}{t^2}\right] \\ &+ C_r'(\cdot)\left[\frac{\partial E_{UC}}{\partial t}\frac{1}{t} + \frac{\partial q_u}{\partial t}\frac{1}{t} - \frac{f}{t^2}\right] - \frac{\partial C_u}{\partial t}.\end{aligned} \tag{A.21}$$

Evaluating at $t = 1$ yields Equation (3.17).

A.2.7 Deriving Equation (3.19)

The Lagrangian of the capped firm problem defined by (3.1), (3.2) and (3.18) is

$$L = p_a a^i + p_f f^i + c^i(e^i_{r0} - e^i_r) + \lambda\left(a^i + a^i_0 + f^i - e^i_r\right) + \mu_{e1} e^i_r + \mu_{e2}(e^i_{r0} - e^i_r) + \mu_a(a^i + a^i_0) + \mu_f f^i + \beta(L - f^i), \tag{A.22}$$

where β is the Lagrange multiplier for the limit constraint. Assuming that the firm makes offsets and permit purchases, the first-order conditions are

$$p_a + \lambda, \tag{A.23}$$

$$p_f + \lambda - \beta. \tag{A.24}$$

Combining (A.23) and (A.24) yields Equation (3.19).

A.2.8 Deriving Equation (3.20)

Differentiating Equation (3.12) with respect to the limit yields

$$\frac{\partial W}{\partial L} = B'(\cdot)\frac{\partial E_{UC}}{\partial L} - C'_r(\cdot)\frac{\partial E_{UC}}{\partial L} + C'_r(\cdot)\frac{\partial q_u}{\partial L} - \frac{\partial C_u}{\partial L}. \tag{A.25}$$

Substituting $p_a = C'_r(\cdot)$ and combining like terms yields

$$\frac{\partial W}{\partial L} = [B'(\cdot) - p_a]\frac{\partial E_{UC}}{\partial L} + p_a\frac{\partial q_u}{\partial L} - \frac{\partial C_u}{\partial L}. \tag{A.26}$$

Substituting Equations (3.8) and (3.11) into Equation (A.26) gives

$$\frac{\partial W}{\partial L} = [B'(\cdot) - p_a]\frac{\partial E_{UC}}{\partial L} + \frac{\partial}{\partial L}\int_{\underline{c}_u}^{p_f}\int_{\underline{e}_u}^{\tilde{e}_{u0}}(p_a - c_u)(e_{u0} - \alpha)dY_u dZ_u. \tag{A.27}$$

Carrying the differential through the second term yields Equation (3.20).

A.3 The Numerical Model

I. Equations

The aggregate cost of emissions reductions function for the capped sector is given by the cost function $C_r(q_r)$. We define costs as

$$C_r(q_r) = \int_{\underline{c}_r}^{\hat{c}_r}\int_{\underline{e}_r}^{\overline{e}_r} c_r e_{r0} dY_r dZ_r. \tag{A.28}$$

We assume that aggregate emissions reductions occur with the cheapest sources first, so that the emission reduction target q_r is achieved at least cost. The term $\hat{c}_r$ denotes the marginal cost of emission reduction necessary to achieve the desired quantity of reductions q_r and is defined by

$$q_r = \int_{\underline{c}_r}^{\hat{c}_r}\int_{\underline{e}_r}^{\overline{e}_r} e_{r0} dY_r dZ_r. \tag{A.29}$$

We assume that unconstrained emissions and marginal costs of emissions reductions are uniformly distributed. Equation (A.29) can be solved for $\hat{c}_r$:

$$\hat{c}_r = \frac{q_r(\overline{c}_r - \underline{c}_r)}{\mathbb{E}(e_{r0})} + \underline{c}_r. \tag{A.30}$$

Substituting (A.30) into (A.28) and evaluating with uniform distributions yields

$$C_r(q_r) = \frac{1}{2}q_r^2\frac{\overline{c}_r - \underline{c}_r}{\mathbb{E}(e_{r0})} + q_r\underline{c}_r. \tag{A.31}$$

We scale the marginal cost of abatement so that $\underline{c}_r = 0$, simplifying the cost function to

$$C_r(q_r) = \frac{1}{2}q_r^2\frac{\overline{c}_r}{\mathbb{E}(e_{r0})}. \tag{A.32}$$

To identify the upper bound of the marginal cost distributions, we differentiate (A.32) and solve for $\overline{c}_r$:

$$\overline{c}_r = \frac{C_r'(q_r)}{q_r}\mathbb{E}(e_{r0}). \tag{A.33}$$

Equation (A.33) calibrates the upper bound of the marginal cost distribution by using data on marginal costs of emissions reductions (C'), emissions reductions (q) and average BAU emissions ($\mathbb{E}(e_{r0})$).

The aggregate cost of emissions reductions function for the uncapped sector is given by the cost function $C_u(q_u)$, where costs are defined as

$$C_u(q_u) = \int_{\underline{c}_u}^{\hat{c}_u}\int_{\underline{e}_{u0}}^{\overline{e}_{u0}} c_u(e_{u0} - \alpha)dY_u dZ_u. \tag{A.34}$$

We assume that aggregate emissions reductions occur with the cheapest sources first, so that the emission reduction target q_u is achieved at least cost. The term $\hat{c}_u$ denotes the marginal cost of emission reduction necessary to achieve the desired quantity of reductions q_u and is defined by

$$q_u = \int_{\underline{c}_u}^{\hat{c}_u}\int_{\underline{e}_{u0}}^{\overline{e}_{u0}} (e_{u0} - \alpha)dY_u dZ_u. \tag{A.35}$$

We assume that unconstrained emissions and marginal costs of emissions reductions are uniformly distributed. Equation (A.35) can be solved for $\hat{c}_u$:

$$\hat{c}_u = \frac{q_u(\overline{c}_u - \underline{c}_u)}{\mathbb{E}(e_{u0}) - \alpha} + \underline{c}_u. \tag{A.36}$$

Substituting (A.36) into (A.34) and evaluating with uniform distributions yields

$$C_u(q_u) = \frac{1}{2}q_u^2 \frac{\overline{c}_u - \underline{c}_u}{\mathbb{E}(e_{u0}) - \alpha} + q_u\underline{c}_u. \tag{A.37}$$

We scale the marginal cost of abatement so that $\underline{c}_u = 0$, simplifying the cost function to

$$C_u(q_u) = \frac{1}{2}q_u^2 \frac{\overline{c}_u}{\mathbb{E}(e_{u0}) - \alpha}. \tag{A.38}$$

To identify the upper bound of the marginal cost distributions, we differentiate (A.38) and solve for $\overline{c}_u$:

$$\overline{c}_u = \frac{C_u'(q_u)}{q_u}(\mathbb{E}(e_{u0}) - \alpha). \tag{A.39}$$

Equation (A.39) calibrates the upper bound of the marginal cost distribution by using data on marginal costs of emissions reductions ($C_u'(q_u)$), emissions reductions (q_u), uncapped sector BAU emissions ($\mathbb{E}(e_{u0})$) and sequestration potential (α).

II. Parameter Values

Table 2 summarizes estimates from the literature that are used to calibrate parameters of the model. Emissions units are reported in million tons of CO_2 equivalent and costs are reported in dollars. Unconstrained emissions from the capped sector are obtained from the 2009 EPA Analysis of Waxman-Markey.

Unconstrained emissions from the uncapped sector are obtained from EPA MAC Curves data file [37]. We assume that the uncapped sector is comprised of agriculture and forestry so that the sum of the two sources equal the value provided in Table 2.[3] Sequestration potential is obtained by evaluating the supply of sequestration offsets at the highest price (211 dollars) reported in the EPA's analysis of domestic offsets potential [37].

Emission reduction values are used to calibrate the slopes of the marginal costs curves for each sector. We evaluate the slope of the marginal abatement cost schedules at 25 dollars. Capped sector emissions reductions are derived from the EPA's simulation of the Intertemporal General Equilibrium Model (IGEM) for the year 2016, yielding an abatement quantity of 864 $MTCO_2e$ when the marginal cost of abatement equals 25 dollars.[4] Uncapped sector abatement at a carbon price of 25 dollars is obtained from EPA Updated Forestry and Agriculture marginal abatement cost curves [37]. We use the estimates from the first decade (2010-2020).

To calibrate the benchmark percentage of offsets that are non-additional, we rely on survey data from the CDM.[5] Table A.1 summarizes recent evidence of non-additional offsets in the CDM.

[3]Other significant sources of domestic offsets come from capturing methane from landfills and coal mines. The EPA forecasts that these types of offsets will comprise less than five percent of the total offsets potential, with the remaining 95 percent attributed to forestry and agriculture [37].

[4]The program significantly expands its coverage in the year 2016 to include virtually all major point sources of CO_2.

[5]We use the percentage of non-additional offsets in the CDM as a proxy for the United States market because it represents the largest and most transparent offsets program in existence and is regarded as the benchmark for new offsets programs.

Table A.1: The Supply of Non-additional Offsets Survey Results

Statement[a]	Percent in agreement[b]
1. Many CDM projects would have also been implemented without registration in the CDM.	71 %
2. Carbon revenues are the icing on the cake, but are not decisive for the investment decision.	86 %
3. Carbon revenues do not significantly increase the profitability of CDM projects.	43 %

[a] Survey questions and results obtained from [105].
[b] CDM Project developers, designated operational entities, individuals from business, research, governments, multilateral non-governmental organizations participated in the survey.

The questions in Table A.1 were asked to project developers and independent auditors of offsets projects [105]. The responses indicate strong evidence of non-additional offsets. For example, the survey results suggest that a majority of credits issued come from projects that would have occurred without the CDM. [105] combines these survey responses with evidence on other CDM projects and concludes that about 40 percent of projects constituting 20 percent of total offset supply are non-additional. Based on Table A.1 and these figures we select a middle-ground estimate and set the percentage of offsets that are non-additional equal to 40 percent. Since there is significant uncertainty on this parameter value, we adjust the percent of non-additional offsets in the sensitivity analysis.

We measure the marginal benefits from emissions reductions with the social cost of carbon.[6] The benefits from reducing emissions can be calculated by multiplying the Social Cost of Carbon by the quantity of reduced emissions. We set the social cost of carbon equal to 25 dollars, reflecting marginal damages from emissions between 2016-2017 at a discount rate of 3 percent [39].

We assume that there is a point mass on the unconstrained emissions distribution for capped firms so that $\underline{e}_{r0} = \overline{e}_{r0} = \mathbb{E}(e_{r0}) = 5,071$.[7] To calibrate the unconstrained emissions distribution for uncapped firms, we deploy an algorithm

[6]The United States Environmental Protection Agency (EPA) defines the social cost of carbon as "an estimate of the monetized damages associated with an incremental increase in carbon emissions in a given year. It is intended to include (but is not limited to) changes in net agricultural productivity, human health, property damages from increased flood risk, and the value of ecosystem services" [39].

[7]Unconstrained emissions heterogeneity among capped firms does not influence the results of our analysis.

that calculates the bounds of unconstrained emissions such that the bounds generate the proportion of non-additional offsets relative to the total offset supply to equal 40 percent given an exogenous carbon price of 25 dollars and a baseline equal to the expected value of uncapped firm unconstrained emissions. The algorithm uses an initial set of bounds to calculate the prevailing percentage of non-additional offsets. If the percentage does not equal 40 percent, it updates the bounds and continues this process until the percent equals 40 percent.

Table 3 shows implied parameter values. The implied parameter values reveal a few points worth highlighting. First, the slope of the marginal abatement cost curve in the capped sector is about twice as shallow as the slope in the uncapped sector, which implies that a majority of abatement is expected to come from capped firms. Second, the gains from allowing offsets will be significant given that the upper bound of marginal costs is lower in the uncapped sector. The marginal abatement cost of the capped sector is lower than that of the uncapped sector by about 50 percent for each abatement quantity. Combining the two MAC curves, however, reduces by the marginal cost of abatement by about 30 percent relative to the case without offsets. This reduction in compliance costs compares to the EPA's analysis of compliance costs with and without offsets. The EPA calculates that compliance costs are 27.2 percent lower with offsets [36].[8] Moreover, our model predicts similar cost savings per ton of offset supplied. At an equilibrium permit price of 25 dollars, compliance costs fall by 14.78 dollars per offset. A

[8]The EPA simulation does not include a scenario without domestic offsets. To determine the cost reduction from domestic offsets, we use simulation output of Scenario 7 - No International Offsets to extrapolate how removing the domestic supply affects abatement costs.

similar calculation using the EPA's analysis achieves cost savings per offset of 13.30 dollars.

III. Equilibrium

The model equilibrium is defined by a price vector (p_a, p_f) that satisfy the following condition:

$$\overline{q} = q_r(p_a) + q_u(p_f) + E_{NA} - E_{UC}(p_f). \tag{A.40}$$

We use the bisection method to search for the price vector that satisfies (A.40).

A.4 Model Validation

We validate the simulation model by comparing equilibrium prices and offset quantities for different reduction targets to EPA analysis of the Waxman-Markey bill that uses the IGEM [36]. IGEM is a deterministic, dynamic general equilibrium model that incorporates banking and borrowing behavior of regulated firms. the EPA assumes that all offsets supplied to the capped sector correspond to mitigation by the capped sector so that there are no over-credited offsets supplied and so that there is no quantity of under-credited reductions. Our model, in contrast, includes supplies of over-credited offsets and has a positive quantity of under-credited reductions. Furthermore, our model is static and does not include banking or borrowing. Nevertheless we demonstrate in this section that our model provides a good approximation to IGEM.

We simulate our model for six different reduction targets that correspond to reported abatement requirements in the bill between years 2018 and 2030. These targets range from 461 $MMTCO_2e$ (year 2018) to $2,850$ $MMTCO_2e$ (year 2030) and encompass the optimal reduction target without offsets that we consider in the paper. The reduction targets requirements and simulation outputs appear in Table A.2.

Table A.2: Model validation

W-M Capped Sector Reduction Target	Permit Allocation	Equilibrium permit/offset price IGEM	This Study	Offset supply IGEM	This Study
461 (year 2018)	4,610	24.42	4.72	333	66
958 (year 2020)	4,113	26.93	14.97	357	208
1,306 (year 2022)	3,765	29.69	22.15	387	308
1,654 (year 2024)	3,417	32.73	29.33	412	408
2,032 (year 2026)	3,039	36.08	37.12	432	517
2,442 (year 2028)	2,629	39.78	45.58	444	635
2,850 (year 2030)	2,221	43.86	53.99	456	752

Results for the EPA IGEM model represent Scenario 7 – No international offsets. The capped sector reduction target corresponds to the required abatement for a given year that is based on business-as-usual emissions projections. Equilibrium prices are reported in (year 2000) dollars. The capped sector reduction target, permit allocation and the offset supplies are reported in $MMTCO_2e$. The reported offset supplies do not include non-additional offsets. The permit allocation is calculated by subtracting the capped sector reduction target from capped sector BAU emissions.

Our model appears to fit the EPA IGEM simulations fairly well. A few differences between modeling outputs and assumptions are worth noting. First, the equilibrium prices are lower in the short run and higher in the long run in our model. For a reduction target of 958 $MMTCO_2e$, our model predicts a permit price of 14.97 dollars while the IGEM model predicts a permit price of 26.93 dollars. This occurs because our model does not incorporate the possibility for the capped sector to bank permits. The EPA predicts that the capped sector would significantly bank permits early to use later in the program. This mechanism has the effect of increasing the scarcity of permits in short-run compliance periods (which raises permit and offset prices) while lowering the scarcity of permits in long-run compliance periods (which lowers permit and offset prices). As a result, the EPA analysis has a flatter trajectory of permit prices. Furthermore, the EPA projects that capped firms would stop banking around 2026, corresponding to the capped sector reduction target that shows a good model fit between our model and the EPA model. In particular, with a capped sector reduction target of $2,032$, the equilibrium permit price predicted by the IGEM model is 36.08 dollars compared to 37.12 dollars in our model. Second, we incorporate a supply of over-credited offsets in our model while the EPA does not. For low capped sector reduction targets, the equilibrium price of offsets will be low, which means that a majority of the supply of offsets is over-credited. The large supply has the effect of depressing the equilibrium price of offsets.

APPENDIX B

APPENDIX FOR *ON THE IMPORTANCE OF BASELINE SETTING IN MARKETS FOR CARBON OFFSETS*

B.1 Introduction

The supporting information includes a detailed description of our analytical framework that underpins the numerical model; definitions of the emissions effects; a formal derivation of the equations that are illustrated in Figure 4.1; a comprehensive description of how we calibrate the analytical model with values from the literature; a description of the numerical model equilibrium and output; model validation that compares benchmark simulation output to other studies in the literature; a section on sensitivity analysis; and a section describing how our sensitivity analysis links back to carbon offset project types.

B.2 Analytical Framework

Here we develop an analytical model to establish the behavior of the economic agents in the model and to define how we calculate the supply of offsets, the supply of over-credited offsets, the quantity of under-credited reductions, equilibrium prices of offsets and permits, and cost savings from including offsets in cap-and-trade programs.

B.2.1 Basic Assumptions

Our simulation results are based on a unified analytical model that links a capped sector with an uncapped sector through a market for carbon offsets. The uncapped sector is comprised of heterogeneous projects. Managers of these projects make profit-maximizing decisions to have their projects opt in to the program by supplying offsets to the capped sector. The capped sector represented by a single cost-minimizing firm. The sector complies with a cap-and-trade program by abating its emissions and purchasing offsets from the uncapped sector.

B.2.2 Capped Sector

The capped sector represents industries likely to be covered under a federal greenhouse gas (GHG) cap-and-trade program. We base our representation on the industries that would have been covered under the H.R. 2454 American Clean Energy and Security Act, henceforth the Waxman-Markey bill, which include coal-fired power plants, petroleum refineries, natural gas refineries, iron and steel production, cement manufacture, among others. The capped sector is regulated by a cap-and-trade program. We model the capped sector as a representative firm that takes equilibrium prices as given. This is a standard assumption used to evaluate compliance costs of cap-and-trade programs [43, 42]. In addition, this approach mimics the outcome of a set of competitive firms [84, 9]. The capped sector is allocated a fixed quantity of emissions permits that are equal to capped sector business-as-usual (BAU) emissions minus a reduction target denoted by $\overline{q}$. To comply with the cap, the capped sector solves the following constrained cost minimization problem:

$$TC = \min_{q,f} \{TAC(q) + pf\} \text{ subject to} \tag{B.1}$$

$$q + f \geq \overline{q}. \tag{B.2}$$

The objective of the capped sector is to minimize total compliance costs (TC), which equal the sum of total abatement costs $TAC(\cdot)$ and the cost of purchasing offsets. The cost of purchasing offsets is the product of the number of offsets purchased (f) and the equilibrium offsets price (p). The capped sector chooses how much to abate (q) and how many offsets to buy to minimize total compliance costs subject to meeting the reduction target, $q + f \geq \overline{q}$. Note that we do not explicitly model the equilibrium permit price. This is because we represent the capped sector as a single, perfectly competitive firm. The equilibrium outcome from our model is identical to the equilibrium outcome from a set of perfectly competitive firms that can trade permits [43, 42]. If we were to explicitly provide a permit price, it would be equal to the marginal cost of abatement of the capped sector in equilibrium [11]. The two conditions for an optimal solution imply that

$$TAC'(q^*) = p, \tag{B.3}$$

or that the capped sector optimal abatement q^* is where the marginal cost of abatement, $TAC'(\cdot)$, equals the equilibrium offsets price. Therefore in equilibrium, the permit and offset prices are identical. Distortions that we do not consider in our model, such as a trade ratio or a limit on the use of offsets, would put a wedge between these prices.

We assume that $TAC'(\cdot)$ is invertible so that condition in B.3 can be solved for q^* as a function of p: $q^* = q^*(p)$. This function defines the equilibrium quantity of abatement by the capped sector.

B.2.3 Uncapped Sector

We assume that there are n potential projects indexed by $i = 1, 2, ..., n$. Each project is managed independently. In our model, managers are the decision makers and are indexed by which project they control, $i = 1, 2, ..., n$. A manager will decide what to do with its potential project based on four project-specific characteristics and the equilibrium offsets price. The four characteristics include the marginal costs of mitigation (c_i), BAU emissions (u_i), sequestration potential (s_i) and an emissions baseline (b_i). Marginal costs are constant and are drawn from a cumulative distributional function $Z(c)$ with support $[\underline{c}, \overline{c}]$. BAU emissions lie within a support $[\underline{u}, \overline{u}]$ where each u_i is independently drawn from the cumulative distribution function $Y(u)$. Project i's sequestration potential is drawn from a cumulative distribution function $X(s)$ that has a support $[\underline{s}, \overline{s}]$, where $\underline{s} < 0$ and $\overline{s} < 0$.

Manager i observes its project's marginal cost of mitigation, BAU emissions and sequestration potential. We assume that the policy maker measures BAU emissions $\tilde{u}_i$ of each project with uncertainty. Project i's predicted BAU emissions, denoted by $\tilde{u}_i$, are equal to BAU emissions plus an emissions shock $\varepsilon_i \sim \mathcal{N}(0, \sigma^2)$:

$$\tilde{u}_i = u_i + \varepsilon_i. \tag{B.4}$$

Each project receives a baseline, b_i, that equals a proportion of predicted BAU emissions:

$$b_i = \alpha \tilde{u}_i. \tag{B.5}$$

The proportion α can be less than, equal to, or greater than one. Managers make opt-in and mitigation decisions for their projects based on the profit function

$$\pi_i = \max_{s_i \leq e_i \leq u_i} \{(p - t_i)(b_i - e_i) - c_i(u_i - e_i)\}, \tag{B.6}$$

where p is the price of offsets and t_i is a project-specific transaction cost per offset awarded. If $\pi_i \geq 0$, then manager i opts in its project to supply a quantity of offsets equal to $f_i^* = b_i - e_i^*$, where e_i^* solves 3.6. Note that e_i^* can be positive or negative, depending on the profitability of each action. A project that sequesters emissions has $e_i^* = s_i < 0$. A project that has e_i set to BAU emissions has $e_i^* = u_i > 0$. This implies that even if $b_i = 0$, project i can supply a positive quantity of offsets. In this case, potential offset supply from project i is equal to the absolute value of s_i. Finally we assume that the policy maker perfectly measures ex-post emissions e_i^* for each project i.

The supply of offsets from project i, denoted by f_i^s, is given by

$$f_i^s = \begin{cases} b_i - e_i^*, & \text{if } b_i - e_i^* > 0 \\ 0 & \text{otherwise.} \end{cases} \tag{B.7}$$

Since each project has a negative sequestration potential $s_i < 0$, even if the project's assigned baseline is equal to zero, they can still mitigate emissions through sequestration, $e_i^* = s_i < 0$. The total supply of offsets, denoted by f, is defined as the sum of offsets from each project:

$$f^s = \sum_{i=1}^{n} f_i^s(p, b_i, s_i, u_i, t_i). \tag{B.8}$$

Since the decision of each manager is dependent on the equilibrium price of offsets, we denote the supply of offsets as a function of this price: $f^s = f^s(p)$.

B.2.4 Equilibrium

We define an equilibrium as an offset price that equates the demand for offsets and the supply of offsets:

$$f^* = f^s(p). \tag{B.9}$$

Plugging this condition into the constraint (B.2) and recognizing that the constraint will be binding at a capped sector problem optimal solution (q^*, f^*), we have

$$q^*(p) + f^s(p) = \overline{q}. \tag{B.10}$$

In our simulation model we assign functional forms to the model's equations so that the functions $q^*(\cdot)$ and $f^s(\cdot)$ satisfy sufficient conditions for a unique p to satisfy equation (B.10). This price will define the equilibrium of our model. Given the equilibrium price, we can calculate capped firm abatement, the supply of offsets and emissions effects that we define in the next section.

B.3 Emissions effects

With this framework, we derive the impact of allowing the capped sector to use offsets for compliance on emissions. We define the impact relative to a hypothetical program that does not permit the capped sector to use offsets. If offsets are allowed to be used for compliance, aggregate emissions may increase or decrease relative to this hypothetical. The change in emissions is dependent on the relative magnitudes of over-credited offsets and under-credited emissions reductions. Next we define these concepts in the context of our model. First we distinguish between two types of offsets: Exact and over-credited. Exact offsets are offsets that correspond to emissions reductions. The supply of exact offsets from project i, denoted by f_i^E, is given by the difference between project i's BAU emissions and its emissions choice:

$$f_i^E = u_i - e_i^*. \tag{B.11}$$

The total supply of exact offsets, denoted by f^E, is defined as the sum of exact offsets from each project:

$$f^E = \sum_{i=1}^{n} f_i^E. \tag{B.12}$$

Over-credited offsets are offsets that do not correspond to emissions reductions. The supply of over-credited offsets from project i, denoted by f_i^{OC}, is given by

$$f_i^{OC} = \begin{cases} b_i - u_i, & \text{if } b_i - u_i > 0 \\ 0 & \text{otherwise.} \end{cases} \tag{B.13}$$

The total supply of over-credited offsets, denoted by F^{OC}, is defined as the sum of over-credited offsets from each project:

$$F^{OC} = \sum_{i=1}^{n} f_i^{OC}. \tag{B.14}$$

The quantity of under-credited emissions reductions from project i, denoted by r_i, is given by

$$r_i = \begin{cases} b_i - u_i, & \text{if } b_i - u_i < 0 \text{ and } e_i^* < u_i^* \\ 0 & \text{otherwise.} \end{cases} \tag{B.15}$$

The total quantity of under-credited emissions reductions, denoted by R, is defined as the sum of under-credited emissions reductions from each project:

$$R = \sum_{i=1}^{n} r_i. \tag{B.16}$$

The change in emissions relative to a program without offsets, ΔE, equals the total supply of over-credited offsets plus the total quantity of under-credited emissions reductions:

$$\Delta E = F^{OC} + R. \tag{B.17}$$

B.4 The Creation of Figure 4.1

Figure 4.1 is constructed by solving the problem of manager i in (B.6). If $c_i > p - t_i$, then project i's marginal cost of mitigation exceeds the net marginal return of mitigation. Therefore the manager has its project perform no mitigation by selecting $e_i = u_i$. In this case, profits are

$$\pi_i = (p - t_i)(b_i - u_i). \tag{B.18}$$

If $b_i < u_i$, indicated by the purple and blue cross-hashed regions in Figure 4.1, then $\pi_i < 0$. In this case, the manager of project i will not opt in its project and will not have it perform mitigation. If $b_i > u_i$, indicated by red region in Figure 4.1, then $\pi_i > 0$. In this case, manager i will opt in its project but will not have it perform mitigation.

Now consider a project that has $c_i < p - t_i$. For this project, the marginal cost of mitigation is less than the marginal return of mitigation for project i. If $b_i > u_i$, indicated by the orange region in Figure 4.1, then $\pi_i > 0$. In this case, manager i will opt in its project and will have it mitigate by selecting $e_i = s_i$. If $b_i < u_i$, represented by the blue and green regions, then the manager's decision depends on the sign of (3.6). The manager will opt in its project and have it mitigate emissions if the returns exceed the costs. The necessary condition for manager i to opt in its project is

$$(p - t_i)(b_i - s_i) - c_i(u_i - s_i) \geq 0. \tag{B.19}$$

The left-hand-side represents project i's profit if its manager chooses $e_i = s_i$, while the right-hand-side represents project i's profit if the manager does not opt it in. Solving (B.19) for c_i yields

$$c_i \leq \frac{(p - t_i)(b_i - s_i)}{u_i - s_i}. \tag{B.20}$$

The non-linear curve in Figure 4.1 represents the case when (B.20) is binding. Managers of projects with marginal costs above the curve do not find it profitable to opt in their project and mitigate emissions, represented by the blue region, while those managers of projects with marginal costs below the curve achieve positive net revenue from opting in and mitigating emissions, represented by the green region.

B.5 The Effect of Project Characteristics and Market Conditions on Potential Project Decisions

To better understand how project characteristics and market conditions influence the decisions of project managers, we present altercations of Figure 4.1 under different scenarios. First, we adjust offset supply potential of a potential project. Second, we adjust baseline stringencies. Third, we present Figure 4.1 under several different market conditions, where projects face different carbon prices or transaction costs.

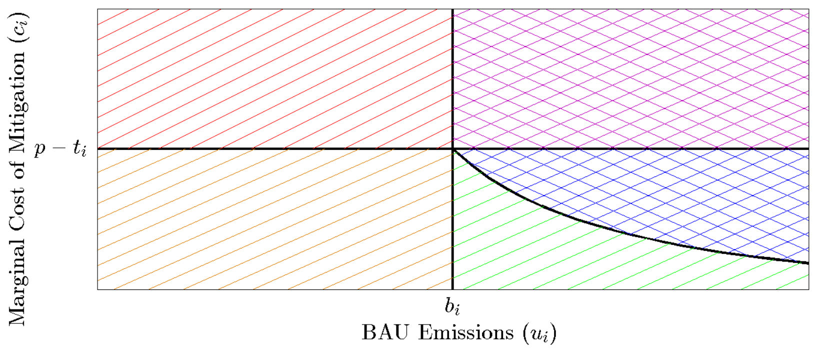
B.5.1 Offset Supply Potential

Figure B.1 displays versions of Figure 4.1 that illustrate different offset supply potentials. In Figure B.1, we vary sequestration potential s_i of potential project i, which maps directly into offset supply potential: a one unit increase in sequestration potential increases offset supply potential by one unit. Moving from

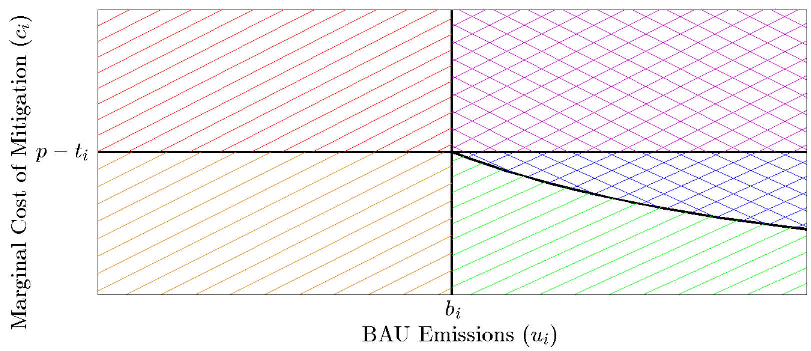
Panels (a) to (c) represents an increase in supply potential, where a hypothetical project described in Panel (a) has a low supply potential. Projects with low supply potential are less likely to opt in (illustrated by the relatively large blue region) and are less likely to be under-credited (illustrated by the relatively small green region. The remaining regions are unaffected. This finding suggests that project types that have a relatively large supply potential are likely to create more under-credited emissions reductions.

B.5.2 Baseline Stringency

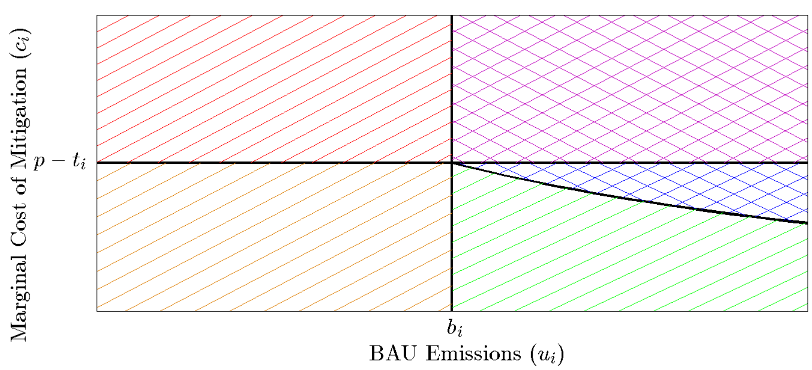
Figure B.2 displays versions of Figure 4.1 that illustrate different baseline stringencies. In Figure B.1, we vary the baseline assigned to project i, b_i, from a high (lenient) baseline in Panel (a) to more conservative, low baseline in Panel (c). Several areas are influenced by the baseline choice. First, as baselines become more stringent (moving from (a) to (c)), the red and orange areas representing a project that is over-credited shrink. This is because a project that faces a relatively low baseline is less likely to have BAU emissions that lie below its baseline. Second, as baselines become more stringent, the purple and blue areas representing a project that is not opted in grow. This is because a potential project that faces a relatively low baseline has less of a profit incentive to be opted in. Third, with a more stringent baseline, the green area representing a project that opts in and that is under-credited may shrink or grow. This is due to two effects at play. The first effect is that a lower baseline makes it more likely that a potential project will be under-credited if it is opted in. This stretches the green area horizontally as seen by moving from Panel (a) to Panel (c). The second countervailing effect is that a lower baseline reduces the incentive for a project with BAU emissions above its assigned baseline to be opted in, which has the effect of reducing the relative green area and increasing the relative blue area in the lower-right quadrant of Figure 4.1. in essence, a lower baseline makes it more likely that a project opting in is under-credited, but it also discourages projects from being opted in.



(a) Low Offset Supply Potential



(b) Medium Offset Supply Potential



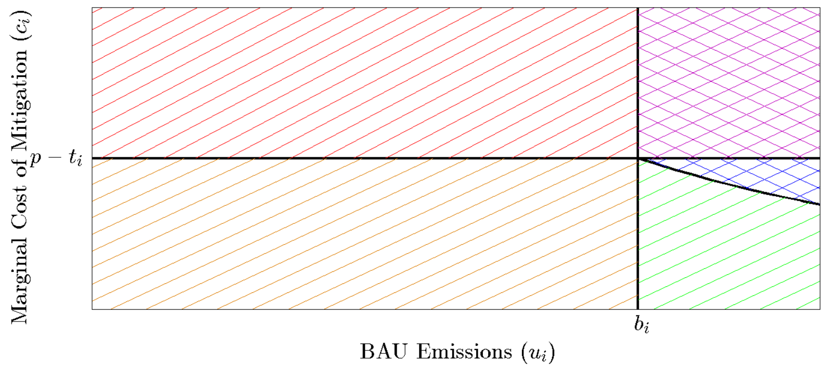
(c) High Offset Supply Potential

Figure B.1: The effect of offset supply potential on potential project decisions

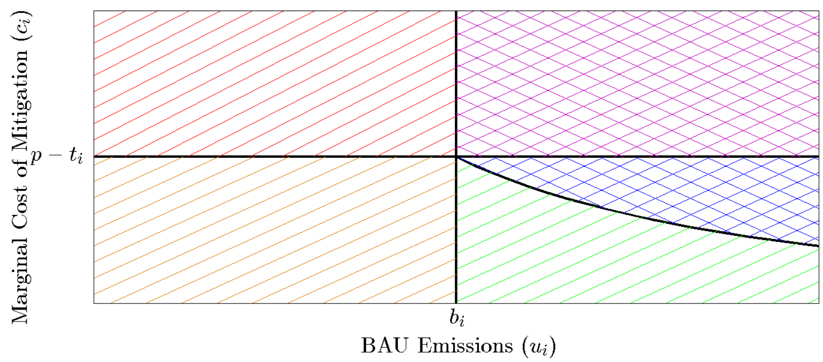
Given that more conservative baselines reduce the over-credited areas and has an ambiguous effect on the under-credited area, we recognize that a marginal reduction of project baselines will likely increase the ratio of under-credited emissions reductions to over-credited offsets. If, however, baselines are reduced enough, the entire area of Figure 4.1 will become dominated by the blue and purple regions as virtually no projects are opted in. Therefore this conclusion is limited to the extent that some projects are still worth opting in.

B.5.3 Net Carbon Price

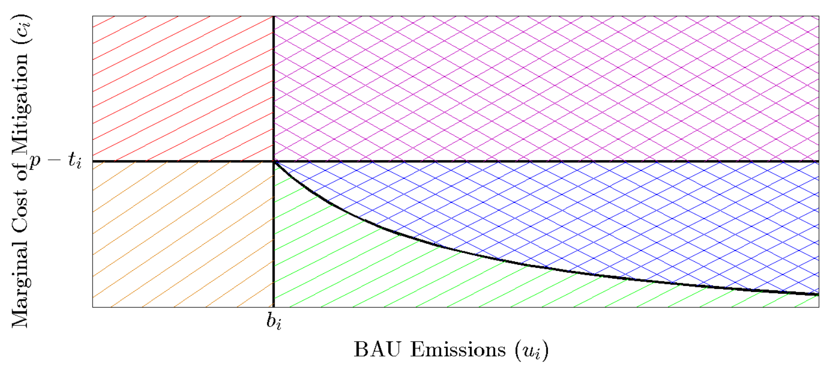
Figure B.3 displays versions of Figure 4.1 that illustrate the effect of different net carbon prices on project decisions. In Figure B.3, we vary the net carbon price faced by project i, $p - t_i$, from a low price in Panel (a) to high price in Panel (c). These panels emerge from either equilibrium market prices for offsets changing or from transaction costs to project i changing. Moving from (a) to (c) represents an increase in the equilibrium offsets prices or a decrease in the transaction cost faced by project i, or a combination of the two. Several areas are influenced by the net carbon price. As the net carbon price increases, projects are more likely to be opted in and to mitigate emissions. This is represented by an expansion of the orange and green regions and a reduction of the red and purple regions. As a consequence, a given project is more likely to opt in and be under-credited. This effect illustrates one of our key results that as carbon prices increase (or as transaction costs fall), less stringent baselines are necessary to balance over-credited offsets with under-credited emissions reductions.



(a) High (Lenient) Baseline

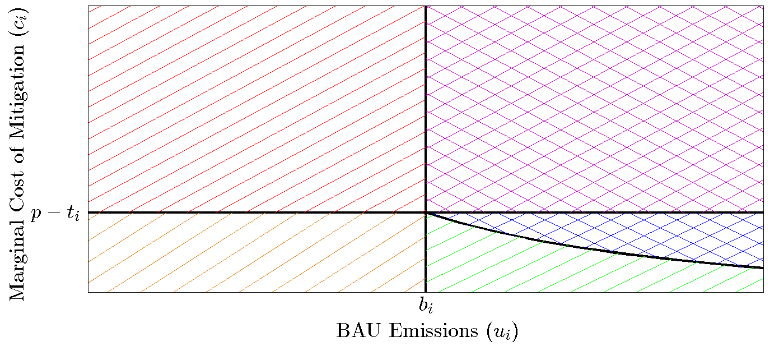


(b) Average Baseline

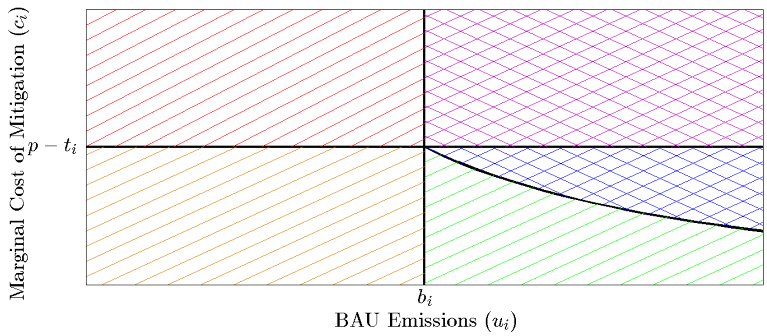


(c) Low (Conservative) Baseline

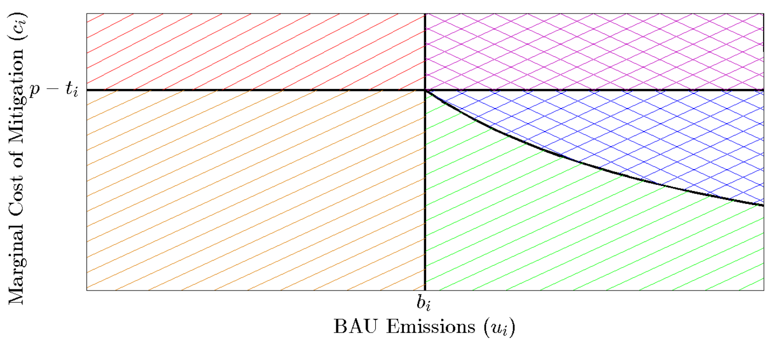
Figure B.2: The effect of baseline stringency on potential project decisions



(a) Low Carbon Price and/or High Transaction Costs



(b) Average Carbon Price and Average Transaction Costs



(c) High Carbon Price and/or Low Transaction Costs

Figure B.3: The effect of equilibrium carbon prices and transaction costs on potential project decisions

B.6 Calibration

The purpose of the numerical model is to yield generic insights that other researchers may apply to a range of climate mitigation programs. Even though our objective is to quantify general relationships, we choose a specific set of parameter values to calibrate the model and assign commonly used functional forms from the literature. Our central values represent emissions and mitigation costs of capped and uncapped sectors in the United States. The analytical equilibrium model is calibrated to observed emissions inventory data and Environmental Protection Agency (EPA) estimates of marginal mitigation costs and sequestration potential [36, 37, 38].

B.6.1 Capped Sector

The capped sector marginal abatement cost function, $TAC'(\cdot)$ is assumed to be increasing with a constant slope that matches processed simulation output of the EPA analysis of the U.S. Waxman-Markey bill [38]. We use processed simulation output from the Intertemporal General Equilibrium Model (IGEM) for the year 2016. We set the slope of the marginal abatement cost schedule equal to 2.83×10^{-8} \$ /ton^2, so that

$$TAC'(q) = 2.83 \times 10^{-8} q, \tag{B.21}$$

where q denotes capped sector abatement in tons of CO_2 equivalent. This implies that the demand for offsets is

$$q^*(p) = \frac{p}{2.83 \times 10^{-8}}. \tag{B.22}$$

Integrating (B.21) and using the endpoint condition that $TAC(0) = 0$ yields a capped sector total abatement cost (TAC) schedule

$$TAC(q) = 1.415 \times 10^{-8} q^2, \tag{B.23}$$

where total costs are denoted in dollars. We assume that capped sector required abatement, denoted by $\overline{q}$, is equal to 500, $2,000$ and $3,500$ representing short, medium and long run targets that are specified in the Waxman-Markey bill[36]. These are approximate reduction targets for years 2018, 2026 and 2034, respectively[36]. To solve for total compliance costs when offsets are not allowed, we substitute the reduction target into (B.23).

B.6.2 Uncapped Sector

We set the number of potential projects equal to $n = 1,000$. This value insures that our fitted marginal cost of mitigation schedule closely approximates EPA marginal cost of mitigation data that we discuss below.

We calibrate the distribution of uncapped sector BAU emissions based on EPA projections of total annual net BAU emissions for the year 2020 [37]. These are defined as the sum of emissions and sequestration among offset sources, which sum to 365 MMTCO2e per year of the program. Total Sequestration Potential is defined as the maximum quantity of sequestration that can occur among offset sources. We obtain a value of $-1,027$ MMTCO2e by subtracting the EPA estimate of the supply of offsets at a carbon price of 211 dollars from Total Net BAU emissions [37]. This value represents an upper bound on the quantity of sequestration that can occur given marginal cost of mitigation estimates [37].

We assume that the distributions for BAU emissions, sequestration potential and marginal costs of mitigation are uniform and independently distributed. Our results are not sensitive to correlation between BAU emissions and sequestration potential but are modestly sensitive to correlation between these variables and marginal costs of mitigation. We provide simulation results for cases when there is negative or positive correlation between these distributions. After we draw BAU emissions and sequestration for each project, we assign marginal costs of mitigation to individual projects so that the resulting mitigation supply function approximates a polynomial fit of the points on the supply curves used in the EPA Waxman-Markey analysis for the year 2020 [36]. These points are plotted in Figure B.4 along with our resulting aggregate supply function.

We take the following steps to assign marginal costs of mitigation. First, we calculate a fifth-order polynomial that fits the points used in the EPA analysis [36]. These points appear in Table B.1 with the corresponding fitted polynomial.

Table B.1: EPA Offset Supply Estimates

Offset Price	Offset Supply
0	0
1	27.4
5	156.4
15	337.5
30	560.9
50	699.5
Fitted polynomial	
$F(p) = 4.2 \times 10^{-2} p - 2.2 \times 10^{-5} p^2 + 1.5 \times 10^{-6} p^3 - 2.9 \times 10^{-9} p^4 + 2.0 \times 10^{-12} p^5$	

Offset prices are reported in dollars per ton of CO_2 equivalent. Offset supplies are reported as million metric tons of CO_2 equivalent.

Next we discretize the fitted polynomial into 101 offset price-supply points starting at the offset price of zero and ending at the offset price of 100. We then define an error function $\Delta(p)$ that measures the point-wise difference between the fitted polynomial and the supply of mitigation schedule from the $1,000$ projects at equilibrium offsets price p:

$$\Delta(p) = F(p) - \sum_{i=1}^{n} f_i^E(p). \tag{B.24}$$

Project marginal costs of mitigation are assigned through the solution to minimizing the sum of squared differences:

$$\min_{c_i, i=1,2,\ldots,n} \left\{ \sum_{P=0,1,\ldots,100} \Delta(p)^2 \right\} \tag{B.25}$$

We use the simplex search method to solve B.25 numerically. The solution to (B.25) yields an uncapped sector supply of mitigation function plotted in Figure B.4. As the figure shows, our algorithm generates a distribution of marginal costs of mitigation that yields an aggregate mitigation function that precisely fits the EPA data.

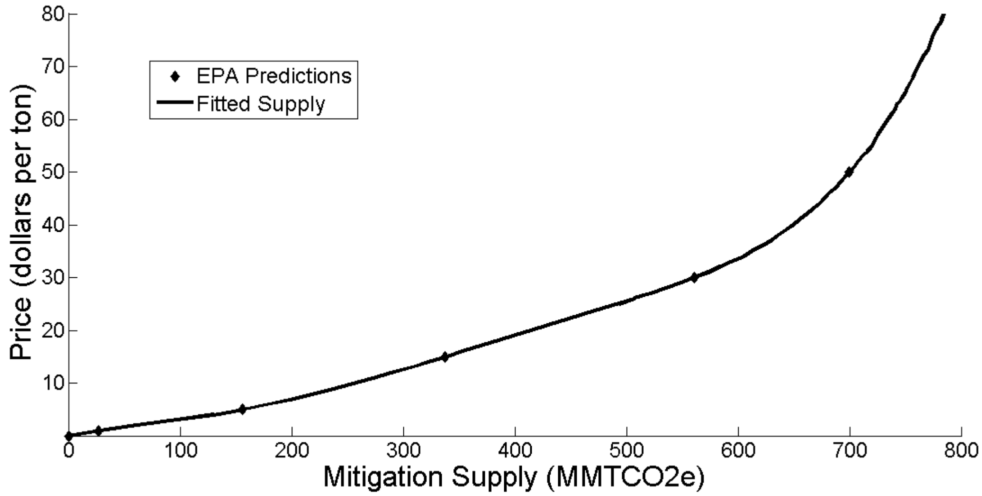


Figure B.4: Calibrated uncapped sector supply of mitigation

The standard deviation of the BAU emissions shocks is set to equal the expected value of BAU emissions. At this value the expected quantity of over-credited offsets equals 30 percent of total offset supply when baselines are set to equal predicted BAU emissions in an equilibrium with a carbon price equal to 25 dollars per ton of CO_2e. We base this calibration on evidence on a meta-study on the Clean Development Mechanism (CDM), the largest operating carbon offsets market [105]. We have three reasons for using estimates from the CDM. First, the CDM is the largest and most transparent carbon offsets program in existence. Second, many other offsets protocols are based on the CDM. Third, there does not exist a comprehensive analysis on the expected supply of over-credited offsets or the uncertainty in predicted BAU emissions for U.S. offset providers. The study estimates that the share of offset supply that are non-additional, or those that do not correspond to mitigation, are about 20 percent [105]. Our definition of over-credited offsets corresponds to how this study and others define non-additional offsets [27]. We calibrate the model such that the benchmark supply of over-credited offsets is 30 percent to account for the fact the composition of domestic projects in a U.S.-based program may be different than the composition of CDM projects (e.g. with the inclusion of U.S. forestry offsets). Moreover, we consider a wide range for the values of the standard deviation of the BAU emissions shocks in Figure 2 and a wider range in the sensitivity analysis to account for the uncertainty for this parameter. Larger standard deviations generally increase the share of over-credited offsets (see Table B.4).

We assign transaction costs to offset projects in line with an analysis of

Waxman-Markey by the Congressional Budget Office (CBO) [71]. The CBO adjusts the offsets supply schedule used by the EPA (in Figure B.4) by adding a 5 dollar per ton of CO2 transaction cost. This value lies within a range of transaction costs estimated in previous work.

Antinori and Sathaye compute transaction costs for 26 carbon offset projects around the world [8]. Their survey includes a variety of offset project types, including forestry, energy efficiency, fuel switching, fuel capture, and renewables. These projects operated between 1991 and 2005 and were verified and monitored through different offset protocols, including the CDM, the Chicago Climate Exchange and Climate Trust. The authors find that transaction costs per ton of CO_2 for the surveyed projects fall within the range of 0.03 per ton of CO_2 and 4.05 per ton of CO_2 with an average of 0.36 per ton of CO_2. Galik et al. estimate transaction costs for US-based forest carbon offset projects [47]. The authors used a detailed spreadsheet model that includes dis-aggregated forest types and 10 different regions. For all project types, transaction costs are estimated to be less than 25 percent of median implementation costs, which the authors define as the sum of production costs and transaction costs. In our model, if projects have transaction costs equal to 20 percent of implementation costs, the median transaction cost per ton of CO_2 is 12.25 dollars, a value that is significantly higher than the range reported in Antinori and Sathaye.

We follow the CBO's approach by assigning a 5 dollar per ton of CO_2 to all projects as this value represents a central value to those reported in research we summarize above. Since there is substantial variability in this value, we perform sensitivity analysis across a wide range of values, including extreme cases of no transaction costs and 10 dollars per ton. We also consider cases in the sensitivity analysis where transaction costs equal a fixed percentage of a project's implementation costs, where implementation costs equal the sum of transaction costs and mitigation costs. These cases imply that total mitigation costs and transaction costs are positively correlated, a condition that is consistent with the estimation results reported in Galik et al.

Our model's calibrated parameter values appear in Table B.2.

Table B.2: Parameter values

Parameter description	Parameter	Value
Lower Bound of BAU emissions	$\underline{u}$	0
Upper Bound of BAU emissions	$\overline{u}$	0.730
Lower Bound of Sequestration Potential	$\underline{s}$	-2.054
Upper Bound of Sequestration Potential	$\overline{s}$	0
Standard Deviation of Emissions Shocks	σ	0.353
Transaction costs	t	5 \$ / ton
Slope of Capped Sector MAC		2.83×10^{-8} \$ / ton^2
Capped Sector Reduction Targets	q	$\{500; 2,000; 3,500\}$

Emissions and sequestration parameters are reported as million metric tons of CO_2 equivalent. The capped sector reduction targets approximately represent years 2018, 2026 and 2034 of the Waxman-Markey bill according to EPA capped sector emissions forecasts [36].

B.7 Numerical Model Equilibrium and Output

Given a sample of BAU emissions shocks, we solve for model outputs by computing a numerical equilibrium for the model. The numerical equilibrium is obtained by solving for an offsets price p that satisfies B.10, which we state again for ease of exposition:

$$q^{*}(p) + f^{s}(p) = \overline{q}. \tag{B.26}$$

In B.26, $q^{*}(p)$ represents the capped sector quantity of abatement, $f^{s}(p)$ denotes the aggregate supply of offsets and $\overline{q}$ is the capped sector reduction target. Substituting the calibrated functions for equilibrium capped sector abatement, $q^{*}(p)$, and the supply of offsets, $f^{s}(p)$, yields

$$\frac{p}{2.83 \times 10^{-8}} + \sum_{i=1}^{n} f_i^{s}(p, b_i, s_i, u_i, t_i) = \overline{q}. \tag{B.27}$$

We use a trust-region reflective search algorithm to solve for the equilibrium offsets price specified by B.26. This algorithm searches for an offsets price that minimizes the distance between the sum of capped and uncapped sector abatement and the capped sector reduction target. The equilibrium offsets price is then fed into the equations for offset supply, emissions and compliance costs. We repeat this process $2,000$ times by drawing $2,000$ different samples of BAU emissions shocks and solving for equilibrium prices and quantities. We average these results and report mean values for the relevant outputs.

B.8 Model Validation

We validate the simulation model by comparing equilibrium prices and offset quantities for different reduction targets to EPA analysis of the Waxman-Markey bill that uses the IGEM [36]. IGEM is a deterministic, dynamic general equilibrium model that incorporates banking and borrowing behavior of regulated firms. the EPA assumes that all offsets supplied to the capped sector correspond to mitigation by the capped sector so that there are no over-credited offsets supplied and so that there is no quantity of under-credited emissions reductions. Our model, in contrast, includes supplies of over-credited offsets and has a positive quantity of under-credited emissions reductions. Furthermore, our model is static and does not include banking or borrowing. Nevertheless we demonstrate in this section that our model provides a good approximation to IGEM.

We simulate our model for six different reduction targets that correspond to reported abatement requirements in the bill between years 2015 and 2040. These targets range from 301 MMTCO_2e (year 2015) to $4,460$ MMTCO_2e (year 2040) and encompass our three reduction targets that we consider in the paper. The reduction targets requirements and simulation outputs appear in Table B.3. We report simulation outputs for the case where transaction costs equal zero to provide a more apples to apples comparison to the EPA simulation.

Table B.3: Model validation

Capped Sector Reduction Target	Equilibrium permit/offset price IGEM	This Study	Offset supply IGEM	This Study
301 (year 2015)	21.10	2.83	312	54
958 (year 2020)	26.93	15.24	357	293
1,828 (year 2025)	34.36	32.95	423	508
2,850 (year 2030)	43.86	57.26	456	633
3,663 (year 2035)	55.98	79.56	534	685
4,460 (year 2040)	71.44	101.61	610	725

Results for the EPA IGEM model represent Scenario 7 – No international offsets [36]. The capped sector reduction target corresponds to the required abatement for a given year that is based on business-as-usual emissions projections. Equilibrium prices are reported in (year 2000) dollars. The capped sector reduction target and the offset supplies are reported in $MMTCO_2e$. The offset supplies provided do not include over-credited offsets. The simulation results presented in this table do not include transaction costs to provide an apples to apples comparison between our model and IGEM.

Equilibrium permit and offset prices are reported in (year 2000) dollars and the capped sector reduction target and the offset supplies are reported in $MMTCO_2e$. For a proper comparison, we report offset supply output that does not include over-credited offsets. Our model appears to fit the EPA IGEM simulations fairly well. A few differences between modeling assumptions are worth noting. First, the equilibrium prices are lower in the short run and higher in the long run in our model. For a reduction target of 958 $MMTCO_2e$, our model predicts a permit price of 15.24 dollars while the IGEM model predicts a permit price of 26.93 dollars. This occurs because our model does not incorporate the possibility for the capped sector to bank permits. The EPA predicts that the capped sector would significantly bank permits early to use later in the program. This mechanism has the effect of increasing the scarcity of permits in short-run compliance periods (which raises permit and offset prices) while lowering the scarcity of permits in long-run compliance periods (which lowers permit and offset prices). As a result, the EPA analysis has a flatter trajectory of permit prices. Furthermore, the EPA projects that capped firms would stop banking around 2025 and 2030, corresponding to the capped sector reduction targets that show good model fits between our model and the EPA model. In particular, with a capped sector reduction target of $1,828$, the equilibrium permit price predicted by the IGEM model is 34.36 dollars compared to 32.95 dollars in our model. Second, we incorporate a supply of over-credited offsets in our model while the EPA does not. For low capped sector reduction targets, the equilibrium price of offsets will be low, which means that a majority of the supply of offsets is over-credited.

The large supply has the effect of depressing the equilibrium price of offsets. This effect is seen by recognizing that the supply of over-credited offsets is 145 $MMCO_2e$, or about three times as large as the supply of exact offsets when the reduction target is 301 $MMTCO_2e$.

B.9 Sensitivity Analysis

We perform sensitivity analysis by examining the key results over a wide range of parameter values. In particular, we vary the uncertainty in predicted BAU emissions, the marginal cost of mitigation from uncapped projects, the correlation between BAU emissions and sequestration potential, the correlation between BAU emissions and marginal costs of mitigation, the correlation between sequestration potential and marginal costs of mitigation, systemic bias in estimating predicted BAU emissions, transaction costs, and transaction costs as a proportion of total implementation costs. Tables B.4, B.7, B.10, B.13, B.16, B.19, B.22 and B.25 report the ratio of under-credited emissions reductions to over-credited offsets for ranges of parameters. Tables B.5, B.8, B.11, B.14, B.17, B.20, B.23 and B.26 report how offset supplies are sensitive to various parameters across the different baseline protocols. These tables report offset supplies relative to the benchmark model output. Tables B.6, B.9, B.12, B.15, B.18, B.21, B.24 and B.27 report how cost savings of including offsets in cap-and-trade programs are sensitive to various parameters across the different baseline protocols. These tables report offset supplies relative to the benchmark model output. The following cases include parameters that are varied around our benchmark assumptions where the capped sector reduction target equals $2,000$ $MMTCO_2e$.

B.9.1 Standard Deviation of Emissions Shocks

The ratio of under-credited emissions reductions to over-credited offsets appears to be sensitive to our assumption on the uncertainty in predicted BAU emissions (see Table B.4). When the standard deviation of emissions shocks is high ($\sigma = 2E[u]$), the ratio falls below one when baselines set to equal 60 percent of predicted BAU emissions. In contrast, when the standard deviation of emissions shocks is low ($\sigma = 0.5E[u]$), the ratio lies above one when baselines are set to 80 percent of predicted BAU emissions. Lower uncertainty requires less stringent baselines to all projects as fewer projects earn over-credited offsets.

Table B.4: Ratio of under-credited emissions reductions to over-credited offsets: Varying the standard deviation of emissions shocks

		Baseline relative to predicted BAU emissions				
		20%	40%	60%	80%	100%
	$E[u]$	46.10	7.12	1.70	0.61	0.28
Standard deviation of emissions shocks (σ)	$0.5E[u]$	201.95	29.19	6.06	1.31	0.35
	$0.75E[u]$	84.44	13.04	2.87	0.81	0.33
	$1.5E[u]$	19.17	2.90	0.89	0.39	0.22
	$2E[u]$	9.27	1.48	0.52	0.27	0.17

Total offset supply is not sacrificed when when the standard deviation of emissions shocks is large (see Table B.5). When the standard deviation is two times as large as it is in our benchmark model, total offset supply declines by only about 10 percent under the maintain environmental integrity protocol, or about 55 $MMTCO_2e$. This result suggests that even when there is significant uncertainty in BAU emissions, maintaining environmental integrity by adjusting baselines down can still be achieved without sacrificing a significant supply of offsets. Table B.6 reports the sensitivity of cost savings from including offsets in cap-and-trade programs as we vary the standard deviation of emissions shocks.

Table B.5: The effect of alternative baseline protocols on offset supply: Varying the standard deviation of emissions shocks

(a) Exact Offsets Supply

		Predicted BAU Emissions	Minimize Supply of Over-Credited Offsets	Maintain Environmental Integrity
	$E[u]$	505	338	497
Standard deviation of emissions shocks (σ)	$0.5E[u]$	+9.11%	+10.65%	+9.66%
	$0.75E[u]$	+4.36%	+5.03%	+4.63%
	$1.5E[u]$	−8.12%	−8.28%	−9.05%
	$2E[u]$	−14.65%	−13.31%	−15.29%

(b) Total Offsets Supply

		Predicted BAU Emissions	Minimize Supply of Over-Credited Offsets	Maintain Environmental Integrity
	$E[u]$	652	338	556
Standard deviation of emissions shocks (σ)	$0.5E[u]$	−4.29%	+10.69%	+4.86%
	$0.75E[u]$	−2.45%	+5.03%	+2.70%
	$1.5E[u]$	+4.75%	−8.28%	−7.01%
	$2E[u]$	+10.89%	−13.61%	−10.43%

Table B.6: The effect of alternative baseline protocols on cost savings from including offsets in cap-and-trade programs: Varying the standard deviation of emissions shocks

		Predicted BAU Emissions	Minimize Supply of Over-Credited Offsets	Maintain Environmental Integrity
	$E[u]$	$20,394$	$9,849$	$16,872$
Standard deviation of emissions shocks (σ)	$0.5E[u]$	-7.97%	$+10.19\%$	$+2.15\%$
	$0.75E[u]$	-3.95%	$+4.77\%$	$+1.27\%$
	$1.5E[u]$	$+8.73\%$	-7.68%	-4.98%
	$2E[u]$	$+17.92\%$	-12.20%	-6.94%

Increasing the standard deviation of emissions shocks increases the difference in cost savings between the protocols. Cost savings increase by about 18 percent under the predicted BAU emissions protocol while they fall by about 7 percent under the maintain environmental integrity protocol when the standard deviation is doubled to $\sigma = 2E[u]$. There are two effects that lead to the larger difference. First, a larger standard deviation increases the quantity of over-credited offsets, which has the effect of lowering compliance costs when offsets are allowed. This is seen by the increase in compliance costs savings for the predicted BAU emissions protocol as σ increases. Second, the quantity of under-credited emissions reductions falls as σ increases, which requires setting more stringent baselines to all projects. More stringent baselines crowd out the supply of over-credited and exact offsets which increases compliance costs.

B.9.2 Supply of Mitigation

We varied the supply of mitigation schedule between one quarter and four times the size of our benchmark model to see how the ratio of under-credited emissions reductions to over-credited offsets depends on the scale of mitigation opportunities in the uncapped sector. Each case represents a scenario where we scale the supply of mitigation schedule at every given offsets price by the percentage denoted in Tables B.7 and B.8. Table B.7 reports the ratio of under-credited emissions reductions to over-credited offsets. The case where we scale the supply of mitigation to 400 percent of the benchmark model represents a program that would incorporate a significantly larger supply of offsets, i.e. international offsets. A greater supply of offsets increases the ratio of under-credited emissions reductions to over-credited offsets. Increasing the supply of mitigation to 200 percent of the benchmark model increases the ratio from 0.61 to 0.96 when baselines are set to 80 percent of predicted BAU emissions. This effect can be explained by the fact that the average project has lower mitigation costs when the scope of offset supply is more broad, which encourages greater project participation to mitigate emissions. This has the effect of increasing the quantity of under-credited emissions reductions.

Table B.7: Ratio of under-credited emissions reductions to over-credited offsets: Varying the supply of mitigation

		Baseline relative to predicted BAU emissions				
		20%	40%	60%	80%	100%
	100%	46.10	7.12	1.70	0.61	0.28
Supply of mitigation relative to the benchmark model	25%	13.36	2.11	0.50	0.18	0.08
	50%	24.96	3.99	0.96	0.34	0.16
	200%	79.12	11.90	2.86	0.96	0.45
	400%	117.19	17.89	4.20	1.41	0.63

Across all protocols, increasing the supply of mitigation dramatically increases exact and total offset supply (see Table B.8). Doubling the supply of mitigation increases total offset supply by between 44 percent and 76 percent. Moreover, increasing the supply of mitigation boosts offset supply relatively more under the environmental integrity protocol than it does under then predicted BAU emissions protocol. Quadrupling the supply of mitigation doubles total offset supply under the predicted BAU emissions protocol while it increases offset supply by 125 percent under the maintain environmental integrity protocol. This is because increasing the supply of mitigation only increases the supply of exact offsets while not affecting the supply of over-credited offsets. As a result, as there become cheaper mitigation opportunities, the supplies under the different protocols become relatively closer.

Table B.9 reports the sensitivity of cost savings from including offsets in cap-and-trade programs as we vary the supply of mitigation. There are two insights from Table B.9. First, as the supply of mitigation increases, the cost savings from including offsets in cap-and-trade programs increases. Doubling the supply of offsets increases the cost savings by roughly 50 percent across the three protocols. This is because with a larger supply comes cheaper reductions for a given offsets price. Second, as the supply of mitigation increases the difference in cost savings between the protocols declines. This is because with a larger supply of offsets, there will be cheaper mitigation opportunities. As a result, the average project is more likely to be opted in even in the face of a baseline below its BAU, creating more under-credited emissions reductions. Hence, baselines can be made less stringent to maintain environmental integrity, leading to increased compliance cost savings.

Table B.8: The effect of alternative baseline protocols on offset supply: Varying the supply of mitigation

(a) Exact Offsets Supply

		Predicted BAU Emissions	Minimize Supply of Over-Credited Offsets	Maintain Environmental Integrity
	100%	505	338	497
Supply of mitigation relative to benchmark model	25%	−71.29%	−72.49%	−73.24%
	50%	−44.95%	−47.04%	−47.08%
	200%	+58.22%	+76.33%	+63.98%
	400%	+125.94%	+140.53	+131.79%

(b) Total Offsets Supply

		Predicted BAU Emissions	Minimize Supply of Over-Credited Offsets	Maintain Environmental Integrity
	100%	652	338	556
Supply of mitigation relative to benchmark model	25%	−55.37%	−72.49%	−71.94%
	50%	−34.97%	−47.04%	−46.22%
	200%	+44.94%	+76.33%	+61.51%
	400%	+97.39%	+140.53%	+125.00%

Table B.9: The effect of alternative baseline protocols on cost savings from including carbon offsets in cap-and-trade programs: Varying the supply of mitigation

		Predicted BAU Emissions	Minimize Supply of Over-Credited Offsets	Maintain Environmental Integrity
	100%	20,394	9,849	16,872
Supply of mitigation relative to benchmark model	25%	−44.31%	−71.53%	−69.07%
	50%	−27.29%	−45.55%	−43.02%
	200%	+39.01%	+70.23%	+54.06%
	400%	+72.55%	+154.38%	+102.75%

Cost savings are relative to a program that does not allow offsets. These savings are reported in millions of dollars for the benchmark model. The remaining cases are reported relative to the benchmark case.

B.9.3 Correlation Between BAU Emissions and Sequestration Potential

We vary the correlation between BAU emissions and sequestration potential from significantly negative correlation ($\rho_{u,s} = -0.8$) to significantly positive correlation ($\rho_{u,s} = 0.8$). Tables B.10 and B.11 report the ratio of under-credited emissions reductions to over-credited offsets and offset supplies for a this range of correlation. The reported results suggest that the model output is insensitive to the correlation between these two random variables. With a correlation of $\rho = -0.8$ and baselines set to equal 80 percent of predicted BAU emissions, the ratio of under-credited emissions reductions to over-credited offsets is 0.57. When the correlation is $\rho = 0.8$, the ratio slightly rises to 0.63 (see Table B.10).

Table B.10: Ratio of under-credited emissions reductions to over-credited offsets: Varying the correlation between BAU emissions and sequestration potential

		Baseline relative to predicted BAU emissions				
		20%	40%	60%	80%	100%
	0	46.10	7.12	1.70	0.61	0.28
Correlation coefficient ($\rho_{u,s}$)	−0.8	47.65	6.93	1.63	0.57	0.27
	−0.4	46.94	7.12	1.71	0.58	0.27
	0.4	46.02	7.32	1.77	0.62	0.29
	0.8	45.60	7.28	1.83	0.63	0.30

Table B.11: The effect of alternative baseline protocols on offset supply: Varying the correlation between BAU emissions and sequestration potential

(a) Exact Offsets Supply

		Predicted BAU Emissions	Minimize Supply of Over-Credited Offsets	Maintain Environmental Integrity
	0	505	338	497
Correlation coefficient ($\rho_{u,s}$)	−0.8	+0.59%	+6.51%	+0.60%
	−0.4	+0.20%	+2.96%	+0.20%
	0.4	−0.20%	−2.96%	−0.40%
	0.8	−0.59%	−6.21%	−0.80%

(b) Total Offsets Supply

		Predicted BAU Emissions	Minimize Supply of Over-Credited Offsets	Maintain Environmental Integrity
	0	652	338	556
Correlation coefficient ($\rho_{u,s}$)	−0.8	+0.31%	+6.51%	−0.18%
	−0.4	+0.15%	+2.96%	−0.18%
	0.4	−0.31%	−2.96%	0.00%
	0.8	−0.61%	−6.21%	0.00%

Table B.12 reports the sensitivity of cost savings from including offsets in cap-and-trade programs as we vary the correlation between BAU emissions and sequestration potential. Again we see that the correlation between these two variables have a negligible effect on the model outputs. Under the predicted BAU emissions protocol, compliance costs savings range from an increase of 0.55 percent ($\rho_{u,s} = -0.8$) to a decrease of 0.37 percent ($\rho_{u,s} = -0.8$).

Table B.12: The effect of alternative baseline protocols on cost savings from including carbon offsets in cap-and-trade programs: Varying the correlation between BAU emissions and sequestration potential

		Predicted BAU Emissions	Minimize Supply of Over-Credited Offsets	Maintain Environmental Integrity
	0	20,394	9,849	16,872
Correlation coefficient ($\rho_{u,s}$)	−0.8	+0.55%	+5.19%	−0.74%
	−0.4	+0.46%	+2.52%	−0.79%
	0.4	−0.21%	−2.68%	+0.07%
	0.8	−0.37%	−5.72%	+0.46%

B.9.4 Correlation Between BAU Emissions and Marginal Costs of Mitigation

We vary the correlation between BAU emissions and marginal costs of mitigation from highly negative correlation ($\rho_{u,c} = -0.8$) to highly positive correlation ($\rho_{u,c} = 0.8$). Tables B.13 and B.14 report the ratio of under-credited emissions reductions to over-credited offsets and offset supplies for a this range of correlation.

With baselines set equal to predicted BAU emissions, a greater correlation between BAU emissions and marginal costs of mitigation increases the relative quantity of under-credited emissions reductions. Increasing the correlation to $\rho_{u,c} = 0.8$ from $\rho_{u,c} = 0$ increases the ratio of under-credited emissions reductions to over-credited offsets from 0.24 to 0.32. A positive correlation between these two variables implies that projects with high marginal mitigation costs have high BAU emissions. Projects with high mitigation costs require a large mitigation potential to opt in if their baseline is below their BAU emissions. These projects, however, will have high mitigation potential because of the imposed correlation. As a result, more projects with baselines below their BAU emissions opt in, leading to a higher quantity of under-credited emissions reductions.

This effect, however, is dominated by a second effect when baselines are set below predicted BAU emissions. Projects with high mitigation costs do not opt in when baselines are set below predicted BAU emissions because the revenue incentive is no longer great enough. At the same time, projects with low marginal costs that have small BAU emissions (due to the imposed correlation) are likely to contribute fewer under-credited emissions reductions. This is because the difference between the baselines and the BAU emissions of these projects is likely to be small, since baselines are positively related to BAU emissions. In other words, a project with low BAU emissions has a lower potential for contributing under-credited emissions reductions. Since projects with low marginal costs are those that opt in, projects that mitigate emissions will provide less under-credited emissions reductions in this case.

Table B.13: Ratio of under-credited emissions reductions to over-credited offsets: Varying the correlation between BAU emissions and marginal costs of mitigation

		Baseline relative to predicted BAU emissions				
		20%	40%	60%	80%	100%
	0	46.10	7.12	1.70	0.61	0.28
Correlation coefficient ($\rho_{u,c}$)	−0.8	1273.79	44.75	3.86	0.70	0.24
	−0.4	185.18	18.34	2.66	0.65	0.25
	0.4	10.75	2.94	1.03	0.59	0.28
	0.8	2.89	1.43	0.78	0.51	0.32

Table B.14: The effect of alternative baseline protocols on offset supply: Varying the correlation between BAU emissions and marginal costs of mitigation

(a) Exact Offsets Supply

		Predicted BAU Emissions	Minimize Supply of Over-Credited Offsets	Maintain Environmental Integrity
	0	505	338	497
Correlation coefficient ($\rho_{u,c}$)	−0.8	−11.49%	−12.72%	−10.66%
	−0.4	−8.91%	−3.55%	−5.03%
	0.4	+2.57%	+0.89%	+1.41%
	0.8	+3.02%	+1.98%	+2.62%

(b) Total Offsets Supply

		Predicted BAU Emissions	Minimize Supply of Over-Credited Offsets	Maintain Environmental Integrity
	0	652	338	556
Correlation coefficient ($\rho_{u,c}$)	−0.8	−7.52%	−12.72%	−14.93%
	−0.4	−6.29%	−3.55%	−7.73%
	0.4	+0.46%	+0.89%	+4.50%
	0.8	+3.22%	+1.98%	+10.61%

Table B.15 reports the sensitivity of cost savings from including offsets in cap-and-trade programs as we vary the correlation between BAU emissions and marginal costs of mitigation. As the correlation between BAU emissions and marginal costs of mitigation increases, cost savings from allowing offsets dramatically falls across all three protocols. Under the maintain environmental integrity protocol, increasing the correlation from $\rho_{u,c} = 0$ to $\rho_{u,c} = 0.8$ reduces cost savings by about 27 percent. This is because projects with high mitigation costs are more likely to opt in while those with low mitigation costs are less likely to opt in when the correlation between BAU emissions and marginal costs of mitigation is positive. Increasing a project's BAU emissions raises its potential revenue from opting in with all other characteristics held constant. Assuming a positive correlation between BAU emissions and marginal costs of mitigation essentially sets BAU emissions low for projects with low marginal costs and sets BAU emissions high for projects with high marginal costs. Relative to our benchmark model where these variables are independent, assigning a positive correlation reduces the profit incentive for low marginal cost of mitigation projects while raising the profit incentive for high marginal cost of mitigation projects. As a result, we see that a positive correlation increases total mitigation costs of projects that opt in, thereby reducing cost savings from including offsets in the cap-and-trade program.

Table B.15: The effect of alternative baseline protocols on cost savings from including carbon offsets in cap-and-trade programs: Varying the correlation between BAU emissions and marginal costs of mitigation

		Predicted BAU Emissions	Minimize Supply of Over-Credited Offsets	Maintain Environmental Integrity
	0	$20,394$	$9,849$	$16,872$
Correlation coefficient ($\rho_{u,c}$)	-0.8	+48.57%	+42.64%	+39.75%
	-0.4	+33.21%	+30.27%	+27.91%
	0.4	−9.97%	−21.19%	−5.70%
	0.8	−30.32%	−47.77%	−26.76%

B.9.5 Correlation Between Sequestration Potential and Marginal Costs of Mitigation

We vary the correlation between sequestration potential and marginal costs of mitigation from highly negative correlation ($\rho_{s,c} = -0.8$) to highly positive correlation ($\rho_{s,c} = 0.8$). Tables B.16 and B.17 report the ratio of under-credited emissions reductions to over-credited offsets and offset supplies for a this range of correlation. The reported results suggest that the model is modestly sensitive to the correlation between these two random variables. With a correlation of $\rho_{s,c} = -0.8$ and baselines set to equal 80 percent of predicted BAU emissions, the ratio of under-credited emissions reductions to over-credited offsets is 0.92. When the correlation is $\rho_{s,c} = 0.8$, the ratio falls to 0.50 (Table B.16). These results suggest that the greater the correlation between sequestration potential and mitigation costs, the fewer the quantity of under-credited emissions reductions. A positive correlation between these two variables implies that projects with low marginal mitigation costs have a high sequestration potential. Projects with low mitigation costs are likely to opt in regardless of their sequestration potential. On the other hand, projects with high mitigation costs require a large mitigation potential to opt in if their baseline is below their BAU emissions. These projects, however, will have low mitigation potential because of the imposed correlation. As a result, fewer projects with baselines below their BAU emissions opt in, leading to a lower quantity of under-credited emissions reductions.

The reason that a negative correlation causes the proportion of under-credited emissions reductions to increase is opposite to the case of positive correlation. Projects with high marginal costs of mitigation are more likely to opt in because they are likely to have a large sequestration potential. As a result, among these projects that are assigned a baseline below BAU emissions have a greater incentive to opt in and contribute under-credited emissions reductions. This can be seen in Table B.16. Increasing the correlation from $\rho_{s,c} = 0$ to $\rho_{s,c} = 0.8$ increases the ratio of under-credited emissions reductions to over-credited offsets from 1.86 to 2.78 when baselines are set to 60 percent of predicted BAU emissions. This relationship is further established in Table B.17. For all three protocols, increasing the correlation between sequestration potential and marginal mitigation costs increases the quantity of offsets from projects mitigating emissions (panel (a)) and total offset supply (panel (b)).

Table B.16: Ratio of under-credited emissions reductions to over-credited offsets: Varying the correlation between sequestration potential and marginal costs of mitigation

		Baseline relative to predicted BAU emissions				
		20%	40%	60%	80%	100%
	0	46.10	7.12	1.70	0.61	0.28
Correlation coefficient ($\rho_{s,c}$)	−0.8	87.69	12.69	2.78	0.92	0.41
	−0.4	71.71	10.44	2.49	0.84	0.38
	0.4	42.55	6.74	1.60	0.56	0.26
	0.8	39.92	6.07	1.48	0.50	0.23

Table B.17: The effect of alternative baseline protocols on offset supply: Varying the correlation between sequestration potential and marginal costs of mitigation

(a) Exact Offsets Supply

		Predicted BAU Emissions	Minimize Supply of Over-Credited Offsets	Maintain Environmental Integrity
	0	505	338	497
Correlation coefficient ($\rho_{s,c}$)	−0.8	−4.95%	−45.27%	−7.85%
	−0.4	−1.98%	−30.47%	−3.62%
	0.4	+11.68%	+20.41%	+11.67%
	0.8	+12.87%	+27.81%	+13.68%

(b) Total Offsets Supply

		Predicted BAU Emissions	Minimize Supply of Over-Credited Offsets	Maintain Environmental Integrity
	0	652	338	556
Correlation coefficient ($\rho_{s,c}$)	−0.8	−4.45%	−45.27%	−3.78%
	−0.4	−1.69%	−30.47%	−1.98%
	0.4	+8.90%	+20.41%	+9.35%
	0.8	+9.97%	+27.81%	+9.71%

Table B.18 reports the sensitivity of cost savings from including offsets in cap-and-trade programs as we vary the correlation between sequestration potential and marginal costs of mitigation. As the correlation sequestration potential and marginal costs of mitigation increases, cost savings from allowing offsets dramatically increases across all three protocols. Under the predicted BAU emissions protocol, increasing the correlation from $\rho_{s,c} = 0$ to $\rho_{s,c} = 0.8$ increases cost savings by about 50 percent. A positive correlation between sequestration potential and marginal costs of mitigation implies that projects with low marginal costs are likely to have very large, negative sequestration potential. The more negative the sequestration potential, the larger the offsets supply potential. As a consequence, assuming a positive correlation implies that very large projects will provide cheap mitigation opportunities while smaller projects are more expensive. Since the projects with low marginal costs of mitigation will opt in, a greater quantity of cheap offsets will be supplied. As a result, the cost savings from including offsets in cap-in-trade programs will be greater.

Table B.18: The effect of alternative baseline protocols on cost savings from including offsets in cap-and-trade programs: Varying the correlation between sequestration potential and marginal costs of mitigation

		Predicted BAU Emissions	Minimize Supply of Over-Credited Offsets	Maintain Environmental Integrity
Correlation coefficient ($\rho_{s,c}$)	0	20,394	9,849	16,872
	−0.8	−57.57%	−66.43%	−45.06%
	−0.4	−46.07%	−64.00%	−39.82%
	0.4	+29.90%	+58.21%	+28.45%
	0.8	+50.11%	+72.75%	+58.70%

B.9.6 Systematic Bias in Predicted BAU Emissions

The benchmark model does not incorporate systematic bias, which is defined as the tendency to consistently over- or underestimate a true value. In this section we investigate the role that systematic bias in estimating predicted BAU emissions may play in the relative magnitude of under-credited emissions reductions. We model systematic bias by augmenting the baseline B.5 with a bias parameter β:

$$b_i = \alpha\beta\tilde{u}_i. \tag{B.28}$$

When there is no bias in estimating predicted BAU emissions, $\beta = 1$ and we are back to our benchmark model. When predicted BAU emissions are consistently overestimated, $\beta > 1$. When predicted BAU emissions are consistently underestimated, $\beta < 1$. In the tables below we report the bias relative to the no bias case. For example, if $\beta = 1.2$, we represent this bias as +20 percent.

We find that systematic bias has a significant impact on relative quantity of under-credited emissions reductions. When there is negative bias in predicting BAU emissions, the ratio of under-credited emissions reductions to over-credited offsets increases. The ratio is about twice as large when the bias is −20 percent compared to the benchmark setting of no bias (see Table B.19. When there is positive bias, the ratio of under-credited emissions reductions to over-credited offsets decreases. The ratio is about half as large when the bias is +20 percent compared to the benchmark setting of no bias (see Table B.19).

Table B.19: Ratio of under-credited emissions reductions to over-credited offsets: Varying systematic bias in predicted BAU emissions

		Baseline relative to predicted BAU emissions				
		20%	40%	60%	80%	100%
	No bias	46.10	7.12	1.70	0.61	0.28
Systematic Bias	−20%	80.34	14.07	3.86	1.34	0.59
	−10%	61.26	9.94	2.55	0.87	0.40
	+10%	38.16	5.22	1.20	0.43	0.21
	+20%	30.08	3.80	0.88	0.33	0.17

Incorporating bias into the analysis shifts the reference point of the baseline. When the bias is positive, the established baseline as a fraction of predicted BAU emissions is not as stringent as in the settings when no bias is present. This effect is quantified in Table B.20. When baselines are set equal to predicted BAU emissions, total offset supply dramatically increases as the bias increases. This increase in offset supply comes from a significant expansion of over-credited offsets. In fact, the supply of exact offsets contracts as the bias increases (panel (a)).

Table B.20: The effect of alternative baseline protocols on offset supply: Varying systematic bias in predicted BAU emissions

(a) Exact Offsets Supply

		Predicted BAU Emissions	Minimize Supply of Over-Credited Offsets	Maintain Environmental Integrity
	No bias	505	338	497
Systematic bias	−20%	+0.79%	0.00%	+1.21%
	−10%	+0.40%	0.00%	+0.60%
	+10%	−0.99%	0.00%	−1.81%
	+20%	−2.38%	0.00%	−2.41%

(b) Total Offsets Supply

		Predicted BAU Emissions	Minimize Supply of Over-Credited Offsets	Maintain Environmental Integrity
	No bias	652	338	556
Systematic bias	−20%	−9.05%	0.00%	+0.72%
	−10%	−4.75%	0.00%	0.00%
	+10%	+3.99%	0.00%	−3.60%
	+20%	+8.90%	0.00%	−1.62%

Table B.21 reports the sensitivity of cost savings from including offsets in cap-and-trade programs as we vary the systematic bias in estimating predicted BAU emissions. Cost savings from including offsets in cap-and-trade programs only appears sensitive to systematic bias in the predicted BAU emissions protocol. Increasing the bias to 20 percent increases cost savings by about 9 percent. This is because a positive bias creates a larger supply of over-credited offsets when baselines do not adjust. When baselines are adjusted in the minimize supply of over-credited offsets and maintain environmental integrity protocols, cost savings are do not dramatically change with different versions of bias. This is because the baseline can be adjusted to account for any bias in estimating predicted BAU emissions. Any positive bias can be account for by lowering the baseline. Likewise, any negative bias can be account for by increasing the baseline.

Table B.21: The effect of alternative baseline protocols on cost savings from including offsets in cap-and-trade programs: Varying the systematic bias in estimating predicted BAU emissions

		Predicted BAU Emissions	Minimize Supply of Over-Credited Offsets	Maintain Environmental Integrity
	No bias	20,394	9,849	16,872
Systematic bias	−20%	−11.33%	0.00%	+0.14%
	−10%	−5.49%	0.00%	0.00%
	+10%	+5.74%	0.00%	−5.23%
	+20%	+11.32%	0.00%	−1.86%

B.9.7 Transaction Costs

We vary the assumption of assigning a 5 dollar per ton of CO_2e transaction cost to each project by considering a wide range of alternative values. All project types, including those that are over-credited and those that are under-credited, are less likely to be opted in when transaction costs are higher since the marginal revenue from supplying an offset is less. We find that higher transaction costs have a mild effect on the ratio of under-credited emissions reductions to over-credited offsets (see Table B.22). Increasing the transaction cost per ton of offsets from 5 dollars per ton to 10 dollars per ton reduces the ratio from 0.28 to 0.24 when baselines equal predicted BAU emissions.

Table B.22: Ratio of under-credited emissions reductions to over-credited offsets: Varying offset supply transaction costs

		Baseline relative to predicted BAU emissions				
		20%	40%	60%	80%	100%
	5	46.10	7.12	1.70	0.61	0.28
Transaction cost per ton of CO_2e	0	51.43	7.70	1.90	0.65	0.31
	2.5	48.65	7.33	1.80	0.61	0.29
	7.5	45.81	6.89	1.64	0.59	0.27
	10	43.76	6.56	1.59	0.54	0.24

Larger transaction costs has the effect of reducing the supply of offsets and lowering the efficiency of incorporating offsets in cap-and-trade programs. We find that projects facing transaction costs are less likely to be opted in to the program. More specifically, we find that projects that supply over-credited offsets and those that generate under-credited emissions reductions are both less likely to participate. The sacrifice in total offset supply by maintaining environmental integrity does not change much when transaction costs are incorporated (see Table B.23).

Table B.23: The effect of alternative baseline protocols on offset supply: Varying the offset supply transaction cost

(a) Exact Offsets Supply

		Predicted BAU Emissions	Minimize Supply of Over-Credited Offsets	Maintain Environmental Integrity
	5	505	338	497
Transaction Cost Per Ton of CO_2e	0	+6.53%	+5.62%	+5.63%
	2.5	+3.56%	+3.25%	+2.82%
	7.5	−3.76%	−2.96%	−3.62%
	10	−11.88%	−6.51%	−7.04%

(b) Total Offsets Supply

		Predicted BAU Emissions	Minimize Supply of Over-Credited Offsets	Maintain Environmental Integrity
	5	652	338	556
Transaction Cost Per Ton of CO_2e	0	+5.06%	+5.62%	+4.14%
	2.5	+2.61%	+3.25%	+1.62%
	7.5	−3.22%	−2.96%	−4.14%
	10	−9.36%	−6.51%	−6.30%

Table B.24 reports the sensitivity of cost savings from including offsets in cap-and-trade programs as we vary the per ton of CO_2 transaction cost. Increasing transaction costs lowers cost savings from including offsets in cap-and-trade programs. The effect, however, is mild. Doubling the per unit transaction cost from 5 dollars per ton to 10 dollars per ton reduces cost savings by about three billion dollars for each protocol, which is approximately a 15 percent reduction. The reason that cost savings are not more sensitive to higher transaction costs is primarily due to the equilibrium offsets price. In these sensitivity runs we assume a medium run capped sector reduction target of $2,000$ $MMTCO_2e$, which creates an equilibrium offsets price of between 38 dollars and 47 dollars per ton. Most projects that are opted in have marginal costs of mitigation well below the equilibrium offsets price, which means that a 10 per ton transaction cost will not discourage them from being opted in. If, however, equilibrium offsets prices are much lower, e.g. 15 dollars per ton, doubling the transaction cost is likely to have a very significant effect on compliance cost savings from offsets.

Table B.24: The effect of alternative baseline protocols on cost savings from including offsets in cap-and-trade programs: Varying the per ton of CO_2 transaction cost

		Predicted BAU Emissions	Minimize Supply of Over-Credited Offsets	Maintain Environmental Integrity
	5	20,394	9,849	16,872
Transaction Cost Per Ton of CO_2e	0	+16.32%	+16.86%	+17.27%
	2.5	+8.02%	+8.85%	+8.33%
	7.5	−7.92%	−8.51%	−9.30%
	10	−12.30%	−17.07%	−17.73%

B.9.8 Transaction Costs as a Fraction of Total Implementation Costs

In our benchmark model we assume that each project faces a fixed transaction cost equal to 5 dollars per ton of CO_2e independent of project characteristics. In this section we relax this assumption by allowing transaction costs be a function of total implementation costs. There is some evidence that projects with low production costs have low per unit transaction costs[47]. Here we assume that transaction costs are proportional to total implementation costs, which are defined as transaction costs plus mitigation costs. Previous literature suggests that transaction costs are under 25 percent of total implementation costs[8, 47]. Therefore we consider the range 0 to 20 percent.

Table B.25: Ratio of under-credited emissions reductions to over-credited offsets: Varying the fraction of implementation costs that are transaction costs

		Baseline relative to predicted BAU emissions				
		20%	40%	60%	80%	100%
	10%	56.08	8.33	2.09	0.74	0.36
Transaction cost fraction of total implementation costs	0%	48.76	7.60	1.88	0.66	0.31
	5%	50.76	7.56	1.82	0.65	0.30
	15%	65.87	9.87	2.44	0.85	0.41
	20%	67.73	10.53	2.55	0.91	0.44

As the fraction of transaction costs increases, the ratio of under-credited emissions reductions to over-credited offsets increases. The ratio increases from 1.88 when there are no transaction costs to 2.55 when transaction costs are 20 percent of total implementation costs with baselines set to 60 percent of predicted BAU emissions. This is because the subset of projects that opt in and earn only over-credited offsets are those that have remarkably high marginal costs of mitigation. (If they had low marginal costs of mitigation, they would have been opted in and performed mitigation.) These projects are disproportionally burdened by increasing the fraction of total implementation costs that come from transaction costs. As a result, fewer over-credited projects are likely to opt in as the fraction increases. This effect is illustrated in Table B.26. Even though exact offsets fall as transaction costs increase (panel (a)), total offsets supply falls much more (panel (b)), suggesting that a significant quantity of over-credited offsets are no longer supplied.

Table B.26: The effect of alternative baseline protocols on offset supply: Varying the fraction of implementation costs that are transaction costs

(a) Exact Offsets Supply

		Predicted BAU Emissions	Minimize Supply of Over-Credited Offsets	Maintain Environmental Integrity
	10%	518	343	506
Transaction cost fraction of total implementation costs	0%	+4.05%	+4.08%	+3.75%
	5%	+1.54%	+2.33%	+1.78%
	15%	−1.54%	−1.75%	−1.78%
	20%	−4.25%	−4.96%	−3.36%

(b) Total Offsets Supply

		Predicted BAU Emissions	Minimize Supply of Over-Credited Offsets	Maintain Environmental Integrity
	10%	640	343	557
Transaction cost fraction of total implementation costs	0%	+6.88%	+4.08%	+4.13%
	5%	+5.16%	+2.33%	+2.15%
	15%	−4.22%	−1.75%	−1.80%
	20%	−7.66%	−4.96%	−2.87%

Table B.27 reports the sensitivity of cost savings from including offsets in cap-and-trade programs as we vary fraction of implementation costs that are transaction costs. Increasing the proportion of implementation costs that are transaction costs lowers cost savings from including offsets in cap-and-trade programs. The effect, however, is even more mild than the effect from increasing a flat transaction cost to all projects (see Table B.24). Doubling the transaction cost fraction of total implementation costs from 10 percent 20 percent reduces cost savings by about 2.5 to 5 percent for the different protocols. Cost savings are not very sensitive to increasing the fraction of total implementation costs that are transaction costs because most projects that are opted in have very low implementation costs to begin with. For example, if many projects have marginal costs of mitigation of 5 per ton of CO_2 or less, then their transaction cost per ton will be under 1 dollar per ton of CO_2 when the fraction is 20 percent, for a total marginal implementation cost of less than 5 + 1 = 6 dollars per ton of CO_2. This increase in implementation costs is relatively small if the equilibrium offsets price is high as it is under a medium run capped sector reduction target.

Table B.27: The effect of alternative baseline protocols on cost savings from including offsets in cap-and-trade programs: Varying the fraction of implementation costs that are transaction costs

		Predicted BAU Emissions	Minimize Supply of Over-Credited Offsets	Maintain Environmental Integrity
	10%	$20,907$	$11,064$	$17,985$
Transaction cost fraction of total implementation costs	0%	+13.69%	+4.59%	+7.79%
	5%	+6.43%	+2.58%	+3.17%
	15%	−4.84%	−2.72%	−1.92%
	20%	−8.25%	−6.21%	−3.41%

B.10 Project Characteristics

In this section of the appendix we describe how the results from the sensitivity analysis can provide guidance to policy makers as they consider which offset project types to include in cap-and-trade programs. We characterize ten different project types by four key parameters that we vary in the sensitivity analysis. These project types are a relevant subset of the entire universe of offset project types. We selected them based on their prominence and acceptance in existing cap-and-trade programs.[71, 23, 1, 105] This analysis serves as a guide for policy makers considering how to treat different project type with regards to baseline stringency, discounting, and outright banning. Although U.S. federal legislation did not specify guidelines on how to treat different project types and which project types would be allowed in Waxman-Markey, we believe that the projects that we consider are an accurate representation of what project types will be considered in any future federal climate change mitigation program that has an offset provision. Table B.28 summarizes the characteristics of the ten project types considered.

Table B.28: Selected Offset Project Characteristics

Offset Project Type	Program	BAU Emissions Uncertainty	Marginal Costs of Mitigation	Offset Supply Potential	Trans. Costs Per Ton of CO_2
Landfill methane capture and destruction [23, 8, 24, 36]	RGGI	Low	Medium	Medium	Medium
Avoided methane emissions from agricultural operations [23]	RGGI	Medium	High	Low	High
Reduction in emissions of SF6 in the electric power sector [1]	RGGI	Low	Low	Low	Low
Sequestration of carbon due to afforestation [8, 36]	AB32	Medium	Low	High	Low
Urban afforestation [8, 24]	AB32	High	High	Low	Low
HFC-23 destruction[120]	CDM	Medium	Low	High	High
N_2O abatement [119]	CDM	Low	Low	High	Medium
Renewable energy [8]	CDM	Medium	Medium	Medium	Low
Energy efficiency [8, 24]	RGGI	Medium/High	Medium	Medium	Medium
Avoided deforestation [8, 24]	REDD+	High	Low	High	Medium/High

Each project type is assigned a qualitative rating for the four key parameters. Our ratings are based on empirical and survey-based studies that we reference next to each project type. We assign a rating for BAU emissions uncertainty, marginal costs of mitigation, offset supply potential and transaction costs. The ratings are relative to the entire universe of offset project types. These ratings, however, are averages and may not apply in all settings. For example, studies have found that marginal costs of mitigation for sequestering carbon from afforestation varies considerably across different regions within the United States[47]. Therefore, we suggest that our results be augmented in a future study with a more rigorous disaggregated and data-driven analysis that quantitatively identifies these characteristics for relevant offset project types.

Our categorization system analyzed with our framework yields some qualitative suggestions for policy makers as they consider including different offset project types for cost containment purposes. First, several project types that have low marginal costs of mitigation are likely to create more under-credited emissions reductions than over-credited offsets awarded to them (see Table B.7 shows the ratio of under-credited emissions reductions and over-credited offsets as we vary the supply (i.e. marginal cost) of mitigation curve, where a larger supply corresponds to lower marginal costs). This is because potential projects with low marginal costs of mitigation are more likely to opt in when they are assigned a baseline below their BAU emissions, as illustrated with the green area of Figure 1. These project types include HFC-23 destruction, N2O abatement, avoided deforestation, and afforestation and SF6 reductions.

This rating dimension makes these projects look desirable not only from an environmental standpoint (as under-credited emissions reductions are more likely to cancel over-credited offsets), but also because of economic concerns. Including these projects in cap-and-trade programs can dramatically reduce compliance costs as much cheaper mitigation opportunities are included under the cap (see Table B.9).

While this result applies to all offset types, its significance is especially relevant for HFC-23 projects. These project types of recently been banned in European Union Emissions Trading Scheme (EUETS) for several reasons, including windfall profits and perverse incentives. These projects, however, have been shown to have exceptionally low marginal costs of mitigation.[120] Our framework predicts that these projects are likely to opt in to an offsets program even when they are assigned a baseline below their BAU emissions. As a consequence, they are likely to generate large volumes of under-credited emissions reductions as long as they are assigned baselines below their BAU emissions. This result may give policy makers pause before they join the EUETS action of disallowing HFC-23 offsets from being used for compliance.

Unfortunately, however, many of the projects that have low marginal costs of mitigation and high offset supply potential also have substantial BAU emissions uncertainty. Table B.4 suggests that as BAU emissions uncertainty increases, there are relatively more over-credited offsets awarded and relatively fewer under-credited emissions reductions created, having the effect of increasing aggregate emissions. Our framework confirms the standard convention of discounting or banning the use of projects with highly uncertain BAU emissions. Among the project types that have low marginal costs of mitigation, N_2O abatement and SF6 reductions appear to also have low BAU emissions uncertainty, strengthening the argument for allowing these types of offsets to be used by the capped sector in emissions trading programs.

To protect emissions caps from being busted and carbon markets from being flooded with over-credited offsets, in the short run when equilibrium permit and offset prices are low policy makers may wish to include projects with low BAU emissions uncertainty or to set highly conservative baselines to all projects to avoid awarding projects with too many over-credited offsets. In the long run, however, when carbon prices are expected to be substantially higher as caps are tightened, policy makers should consider relaxing baselines and including potentially risky projects with medium or high BAU emissions uncertainty and low marginal costs of mitigation, including HFC-23 destruction and forestry related offsets.

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